NOVEL METHOD OF DIGITIZATION OF ELECTROCARDIOGRAM SIGNALS

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NOVEL METHOD OF DIGITIZATION OF ELECTROCARDIOGRAM SIGNALS

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SUMMARY

The objective of the proposed research was to implement a novel digitization tool which extracts electrocardiogram (ECG) signals, as well as patient demographic information from paper electrocardiography records. A MATLAB (MathWorks: Natick, MA) based graphical user interface (GUI) application was proposed wherein the electrocardiogram (ECG) signals are digitized based on an algorithm built upon previous work by Ravichandran et al. [7]. The existing algorithm carried out Optical Character Recognition (OCR) for the extraction of the demographic information from the record. In addition to this existing function, the proposed research aims to implement OCR on the ECG character lead names in order to further enhance the accuracy of the digitized ECG signals. The proposed algorithm was subjected to a reader study conducted at Emory University. In order to measure the correlation between the digitized ECG signals and the paper ECG records, the reader study aimed to measure the following parameters: *QT* (the time measured from the *QRS* complex to the end of T-wave), *QRS* (the duration measured along the length of the *QRS* complex), *PR* (the time measured from the beginning of the P-wave to that of the *QRS* complex), QT_c (the increase in duration of action potential of signal) and *RR* (the time measured between 2 consecutive R-R peaks). From the intra-observer and inter-observer correlation values between the digitized and paper ECG records ranged between 0.2557 to 0.9371. Although the *RR* intervals was found to be statistically significant, the *QT* and QT_c intervals were not. The kappa statistic ranged between -0.4886 to 0.8742, for the intra-observer measurements. For the inter-observer measurements, the kappa statistic ranged between 0.1722 and 0.8216.

CHAPTER 1

INTRODUCTION

Electrocardiograms (ECG), introduced by William Einthoven, have been used extensively since 1901 to record the electrical signals of the heart [1] (**Figure 1.1**). This has enabled the medical community to detect and diagnose with greater accuracy, the abnormalities of the heart such as cardiac arrhythmias, myocardial infarction, and heart failure [2].

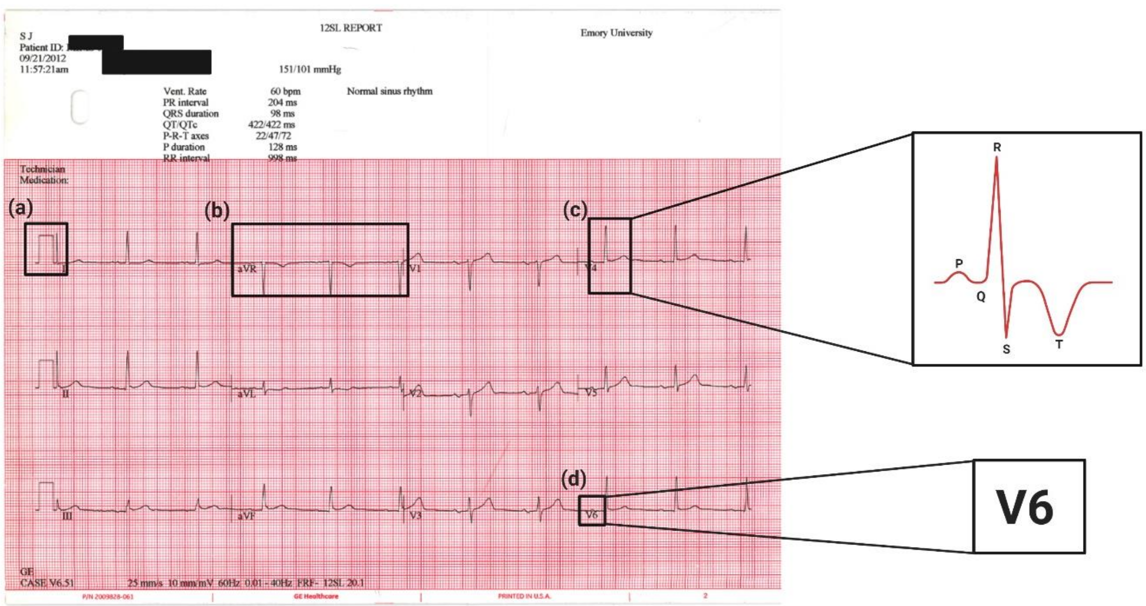

Figure 1.1 Salient points of interest on the ECG that is relevant to the thesis are described. (a) The patient information is typically placed in the top section of the ECG record. (b) In this example, the ECG signal information is placed below the patient demographic section of the ECG record. (c) The ECG segments are preceded by a DC pulse, for calibration purposes. (d) As depicted, a typical ECG segment consists of 3 consecutive heart beats. (e) Each heartbeat is characterized by the peaks *P, Q, R, S* and *T*. (f) Each ECG segment has an ECG lead character name associated with it for identification purposes. Note, all identifying patient information has been removed.

Although ECGs were previously exclusively recorded on paper, ECG machines are now able to produce time series ECG data (amplitude and time) along with the corresponding paper ECG record, which is often scanned and stored in digital format [3]. Given that there still exists a substantial number of paper ECG records which have not been digitized yet, there has been a multitude of algorithms proposed to efficiently convert paper ECG records into digitally stored ECG signals [4]. Electronic Medical Records (EMR) are being used increasingly to track patient information and store ECG records digitally [5]. Integrating EMR with the digitized ECG signals would potentially help accumulate the necessary information for prediction algorithms. Digitizing paper records and combing it with EMRs is now essential since machine learning and data analysis algorithms are used to extract relevant information that help improve prognosis of cardiac diseases [6].

Digitization of paper ECG records is the process of extracting the 2-dimensional image of the ECG signal from the scanned ECG record, into a 1-dimensional time series signal. Utilizing paper ECG records for retrospective analysis would be inefficient since the process would be manually implemented, the paper degrades over time unless preserved carefully, and the ink often fades. However, the scanned paper ECG records poses complications of additional noise during scanning process, varied lighting conditions and more storage when compared to digitized ECG signals [9]. Due to the varied nature of problems that arise during digitization, it is difficult to implement an algorithm which can accommodate the problems in a computationally efficient manner.

The objective of this work is to implement a novel digitization tool which extracts ECG signals, as well as text-based patient demographic information from paper electrocardiography records. A MATLAB (MathWorks: Natick, MA) based graphical user interface (GUI) application is proposed that builds upon and extends a signal processing algorithm previously developed by Ravichandran et al. [7]. An additional feature of this thesis is to develop an Optical Character Recognition (OCR) for the extraction of ECG character lead names in order to further enhance the accuracy of the digitized ECG signals [8].

The proposed digitization algorithm involves preprocessing of the ECG records, extraction of patient demographic information and finally the extraction of the digitized ECG signal, as depicted in the flowchart (**Figure 1.2**). This involves performing morphological operations like thresholding and filtering, after which an OCR algorithm is used to extract the text-based demographic information. This algorithm is then packaged into an open source standalone application which carries out the digitization of scanned paper ECG records. The algorithm was validated by a clinical study conducted at Emory University. The clinical study aims to measure the correlation between the digitized ECG record and the paper ECG record.

This work attempts to address two main research questions. The first being the lack of an open source software that implements the process of ECG digitization. The second being the complete removal of the disturbance caused to the digitized signal by overlapping lead characters on the ECG signal, which contribute to a significant skew in the digitized signals.

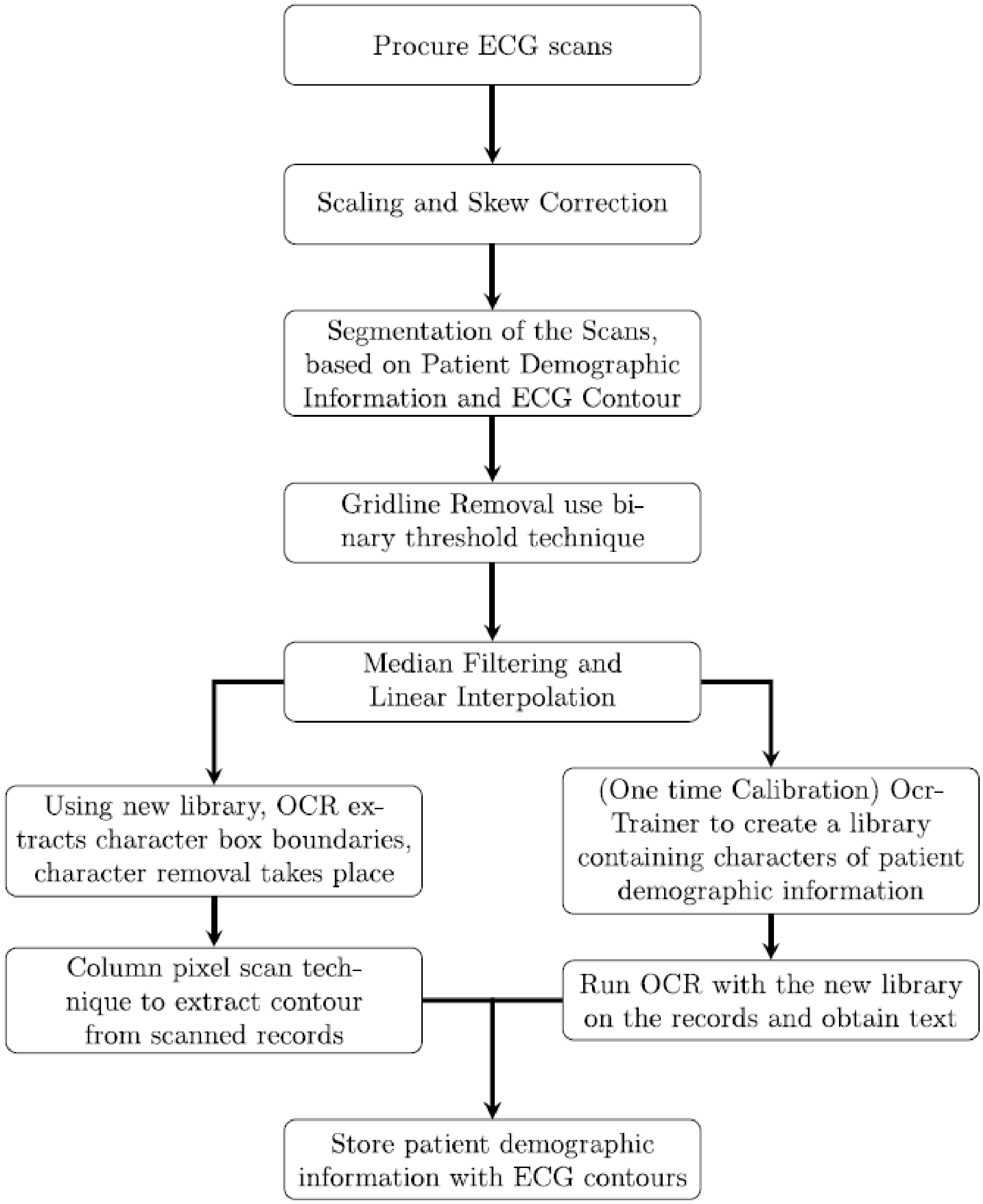

Figure 1.2 The steps involved in the proposed digitization of scanned ECG records.

The thesis is organized in the following manner. Chapter 2 reviews the current literature and identifies gaps related to digitization of ECG records. Chapter 3 explains the methodologies used in the implemented algorithm, with a focus on the GUI implementation. Chapter 4 presents and discusses the results of the reader study. Lastly, chapter 5 addresses limitations of the current algorithm, and potential future applications for consideration.

CHAPTER 2
LITERATURE REVIEW

ECG signals continue to be printed on paper at many healthcare institutions, even though digital formats were popularized starting from the late 1990's. With the increasing digitization of healthcare records, digital storage methods are increasingly being pursued for ECG signals. This is due to advantages such as greater storage capacity, easy transportability and access. The wide variability in the models of ECG machines, and the proprietary interests of ECG manufacturers contribute to the lack of an universal digital format till date [10,11]. There have been many attempts to standardize ECG formats by organizations such as the American heart Association [12], and Common standards for Quantitative Electrocardiography [13].

This has inspired efforts over the past few decades to formulate various algorithms that digitizes ECG signals from scanned ECG paper records. Each of these algorithms has its own advantages and disadvantages [9]. Upon investigation, it is apparent that there are commonalities between the skeletal structure of the algorithms. They can be partitioned into preprocessing of paper ECG records, removal of background, noise removal and extraction of ECG signal. At the outset of preprocessing of data, some algorithms use the color information of the ECG records [14,15], while others convert them into grey scale [16,17]. While algorithms involving color extraction can be useful if the ECG records are particularly degraded, grey scale processing is the most computationally efficient and hence is preferred [15].

Additional techniques such as correction of the skewed angle of the ECG record have been proven to be useful. With respect to background removal of ECG grid, algorithms generally involve the application of a variation of a filter on the ECG record, and separation of the ECG signal from the grid based on characteristics such as color, or intensity value [7,18,19]. There have been numerous algorithms proposed for the extraction of the ECG signal, such as eight-neighbor tracing [16], anchor point setting [18] and column-wise pixel scan [7] to name a few. Any permutation of the mentioned algorithms from their respective categories would often lead to a reasonably accurate estimate of the ECG signal, keeping in mind constraints such as the minimum resolution of the scanned ECG records. Depending on the minimum level of accuracy desired, and the degree of computational efficiency required, a few of the algorithms can be potentially chosen for future use.

The current advancements in the digitization of ECG signals focus on integrating the data extracted with existing medical databases, batch processing of ECG records and strive towards higher accuracy of digitized ECG signals with minimal human intervention during the process. For instance, Ravichandran et al. utilized OCR for extraction of patient demographic information, to link it to the EMR of the patient [7]. Mohammed Baydoun et al. proposed a method of ECG signal extraction which can be executed regardless of resolution of the ECG records, along with automatic lead detection of ECG signals [20]. X Sun et al. proposes to extract 12 ECG segments simultaneously, using Connected Component Analysis [21].

One of the issues that has not be brought up by the algorithms discussed thus far are the removal of overlapping lead characters on the ECG signal. Dharmendra Gurve et al. proposes removal of watermarks by the extraction of the numerical coordinates of the scanned ECG records [22]. This has not been validated through a standard procedure, and there is no discussion of statistical evidence to confirm the robustness of this approach. Arttu Holkeri et al. utilizes the ECG Trace Tool to manually remove the text on ECG signals, and this must be done individually for each scanned ECG record, which is inefficient [23]. Hla Myo tun et al. proposes removal of characters using a combination of region segmentation and morphological processes for resolutions of ECG higher than 300DPI [24]. Although promising in terms of results, there is again no validation study or statistical evidence to back this up.

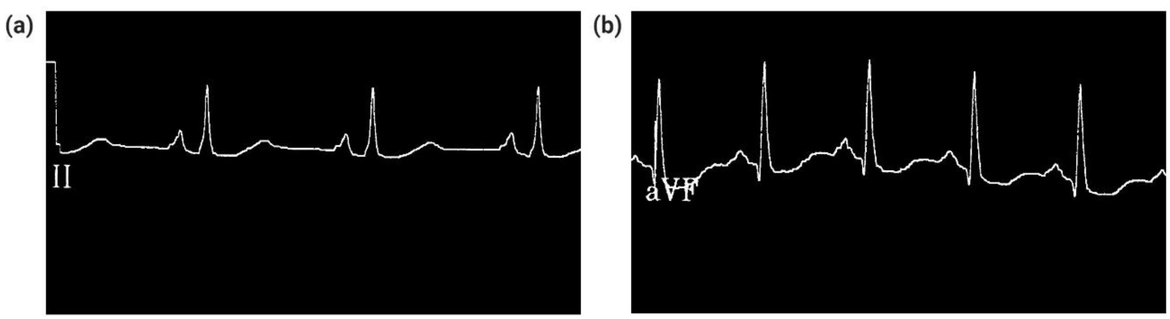

Figure 2.1 The ECG records subjected to thresholding and grid removal are displayed to illustrate the issue of overlapping text on ECG signals. (a) The ECG lead character ‘II’ is well separated from the ECG signal. (b) The ECG lead character ‘aVF’ is overlapping with that of the ECG signal.

Despite the number of algorithms available, there have not been many attempts dedicated towards establishing an open source software for digitization of ECG records. None of the algorithms thus far also claim that digitization of all varieties of ECG templates is possible. The open source codes established so far deal with the extraction of ECG signals from pdf version, and not from the scanned ECG images [22,25,26]. Hence it does not address the issue at hand. An ECG trace tool was implemented with many functionalities, but unfortunately is still not available to the general public [23]. Apart from the above, there are a few GUIs proposed in literature, but it is not made clear when the software would be open source [20,22]. There has also been an android application developed, but a study has not been conducted to verify its robustness [27]. Appendix D contains a table which elaborates on a few of the novelties, and limitations of selected reviewed papers.

From the literature survey conducted, it is apparent that there are 2 main issues that are required to be tackled. The first being the lack of an open source software that implements the process of digitization of ECG signals from ECG records. The second being the complete removal of the disturbance caused to the digitized signal by overlapping lead characters on the ECG signal. Building upon on an algorithm by Ravichandran et al. [7], the thesis will be an attempt to address those problems.

CHAPTER 3

METHODOLOGY

In order to digitize the paper ECG records and extract the patient demographic information the following open source standalone application is proposed. The distinguishing feature of this algorithm is that the OCR function is implemented for the removal of irrelevant characters overlapping with the ECG signal in the paper ECG record. This proposed algorithm is elaborated in the following paragraphs.

Section 3.1: Preprocessing Steps

The scanned paper ECG records were initially converted into gray scale 8-bit 300dpi images since it reduces the storage space required without compromising the quality of the resulting digital ECG records. While processing the scanned ECG records, a few tend to be scanned at an angle with respect to the horizontal, as a result of which a transformation of the image is required to correct this skew. This angle of skew (θ) is detected by utilizing the grid lines found in the background of ECG records. By using the concept of Hough transform, and the associated parametric transformation equation, the angle of skew can be estimated **(Equation 3.1)** [28]. The parameters θ and r are the angle of the line and the distance from the line to the origin, respectively. It is necessary to test all the ECG records in a batch for a change in angle.

$$r = x(\cos\theta) + y(\sin\theta) \tag{3.1}$$

In a typical ECG record, there are 2 main regions. The first is the region containing the patient demographic information, while the second is the area containing the ECG signal information. The former is referred to as the “Demographic Region” and the latter is referred to as the “Contour region” (**Figure 3.1**). In the GUI implemented, the coordinates of the Contour and Demographic region are user defined. The predefined coordinates for a template are then used to segregate the ECG segments.

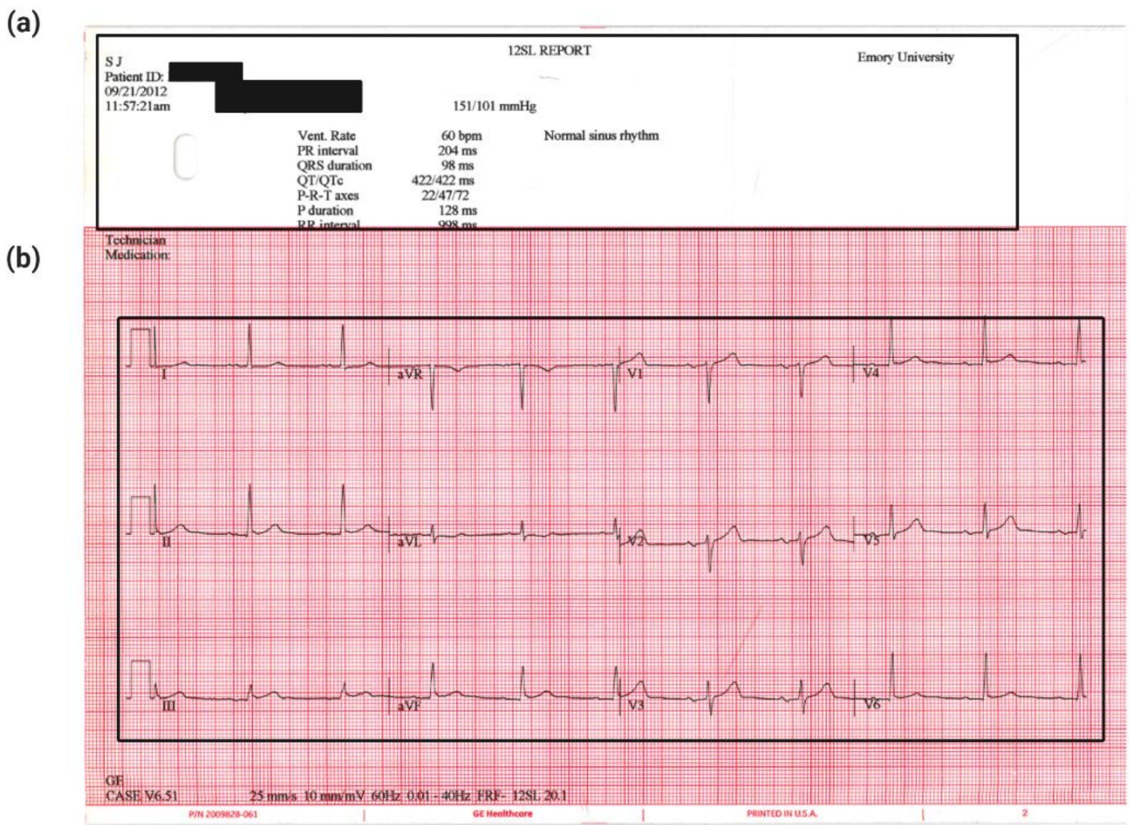

Figure 3.1: A typical template of an ECG record is displayed. (a) The patient information is highlighted in the “Demographic Region” (b) The ECG signal information is contained in the “Contour Region” of the ECG record. Note, all identifying patient information has been removed.

Since there exists a wide variety of ECG templates, and due to problems, such as faded ink and degraded paper, detection of the contour and demographic regions by the algorithm alone may not be reliable [15]. The GUI comes preloaded with a set of ECG templates, which in this case are for the ECG machine templates GE CASE V6.51 and MAC500K 003A (General Electric Company; Boston, MA). The user can continue to add new templates to the application (**Figure 3.2**). An option will be provided in the GUI to choose the kind of template required, or to enter a new template. If a new template is entered, the user will be required to perform a one-time calibration in the GUI.

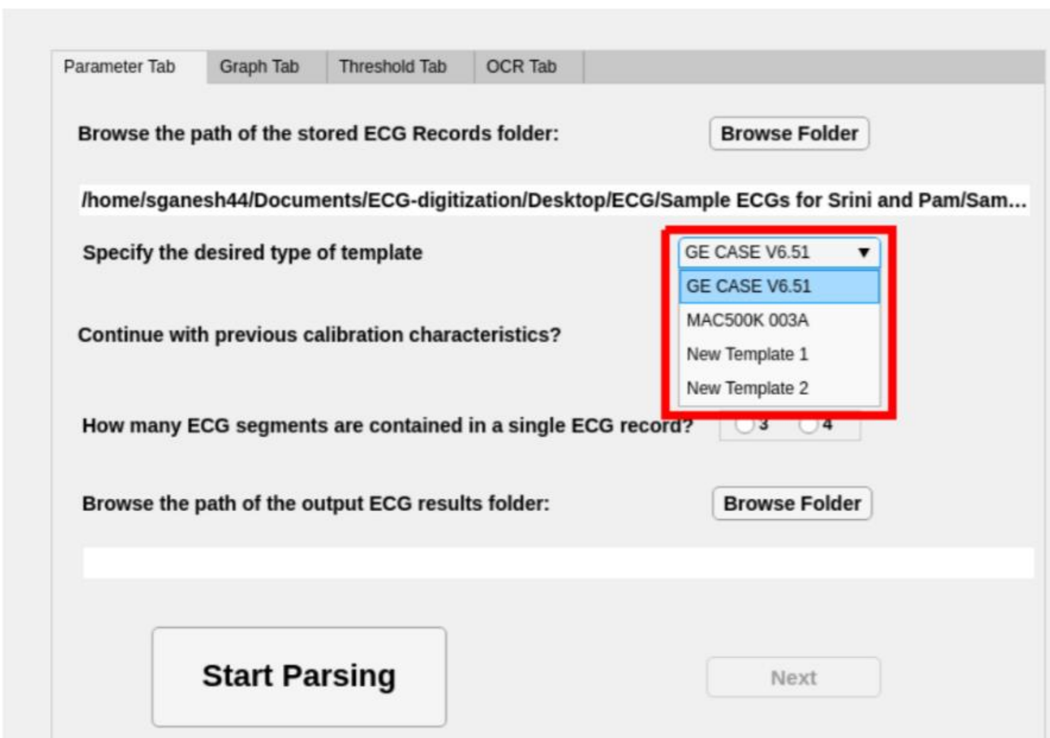

Figure 3.2 A screen shot of the "Parameter Tab" of the proposed GUI is depicted. The options for the type of template to be selected is highlighted.

Section 3.2 Extraction of ECG signals

In the Contour region, the gray scale ECG leads are separated from the background grid by a binary thresholding technique. Although a threshold value can be fixed either based on the template chosen, or by analyzing the histogram of a sectioned grid region of the graph, irregular illumination of the document can affect the threshold value. Moreover, it may be necessary to model the threshold value as a function of length across the record, as the illumination may change based on the placement of light source at the time of scanning. Due to the reasons mentioned, the user can instead select a threshold value for a batch of ECG records, which is depicted (**Figure 3.3**).

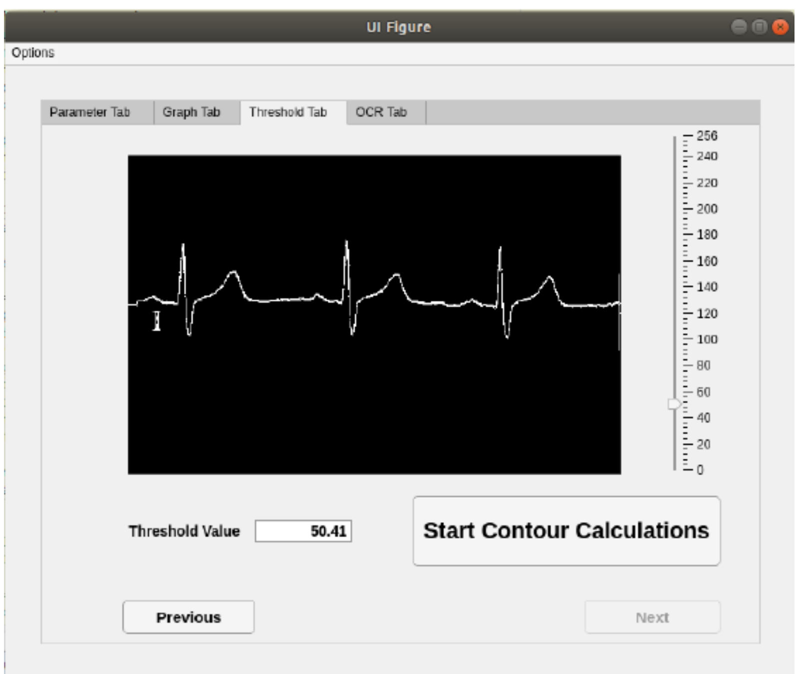

Figure 3.3 Screenshot of the “Threshold Tab” of the proposed GUI. The slider at the extreme right of the figure is used to decrease or increase the degree of filtering.

Following the background grid removal, noise removal is undertaken using a median filter to remove salt and pepper noise, and linear interpolation to bridge discontinuities in the ECG leads. ECG leads are extracted by scanning each of the columns and storing the coordinates of the pixels. A 12-lead ECG segment typically has 4 rows, with each row referred to as a segment. Each new segment in an ECG record typically contains information from 3 to 4 ECG leads, each preceded by a DC pulse (**Figure 3.4**). The number of ECG segments in a graph depends on the type of template. The time-voltage pairs are thus obtained for each pixel of the ECG signal, and the digital ECG signal is hence extracted.

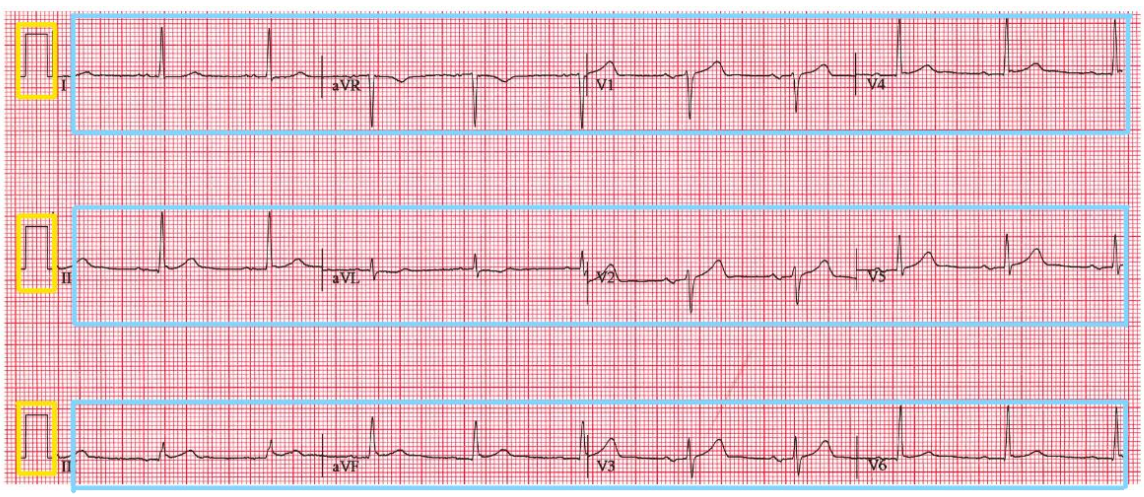

Figure 3.4 The yellow squares depict the DC pulses, which are used to scale the ECG signal. Each of the highlighted blue rectangle contain 4 ECG leads in a row.

Section 3.3 OCR on ECG Records

The underlying principle of Optical Character Recognition (OCR) is to identify characters in the image using a predefined template library, in order to determine which of the OCR template characters it has maximum correlation with. The OCR application available in MATLAB is used to make an OCR template library for different varieties of ECG records. An OCR template library should ideally contain lower and upper cases of the English alphabet, and the 10 main digits of numeric characters. It should be noted that for a specific type of ECG record, the template library used to extract the patient demographic information is not necessarily the same as the template library for the removal of characters.

OCR is used for two main purposes in the algorithm. The first purpose is to extract the patient demographic information and thus link it to the EMR of a patient [8]. The extracted patient demographic information is stored in the form of a text file. The demographic region of the ECG records is initially binarized and subjected to morphological techniques such as erosion and dilation. A reduced skeletal representation of the text contained in the demographic region is generated. The next step focuses on the creation of an OCR template library specific to the ECG records. For annotation purposes, the OCR application identifies characters based on a pre-existing English template library. Manual annotation is carried out for those characters which are misidentified or overlooked (**Figure 3.5**). The library is then trained and tested on the available ECG records. The extracted characters are stored in a text file.

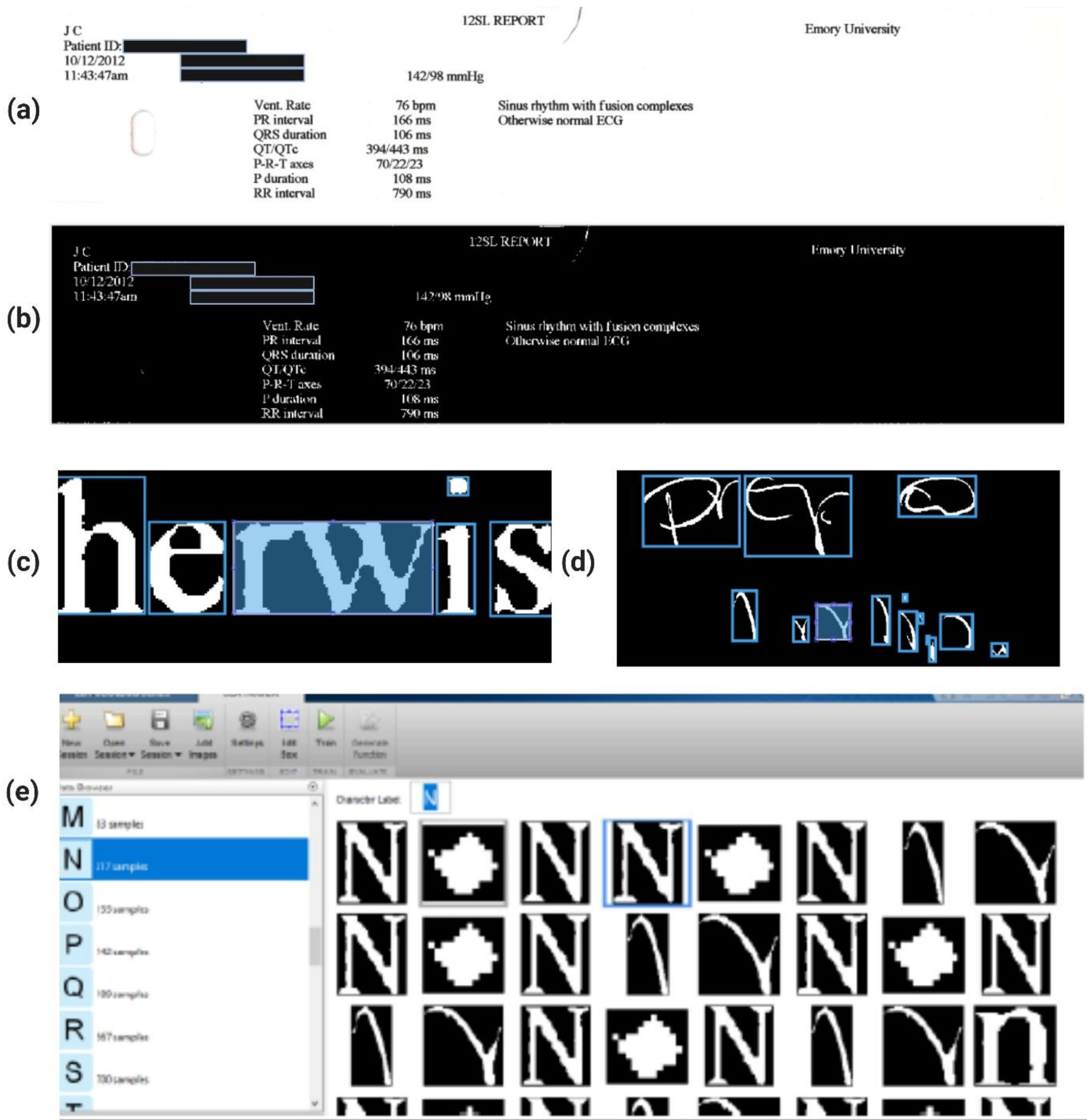

Figure 3.5 The steps involved in creation of an OCR template for the ECG records is shown. (a) The demographic region of a typical ECG record is shown. (b) The demographic region is preprocessed using thresholding and morphological techniques. (c) The OCR application identifies and annotates individual characters wherever possible. (d) Handwritten characters often are not recognized due to partial removal of lines after the preprocessing step, and hence are categorized as non-text. (e) The annotated characters which are misclassified or overlooked can be annotated again. Note, all identifying patient information has been removed.

The second purpose of utilizing OCR is to remove ECG lead characters which are near the ECG signal of interest. The contour region is subjected to binarization, grid removal and segmentation of the ECG records. The steps that follow are identical to those applied on the demographic region for identification and annotation of the characters. The coordinates of bounding boxes of the identified characters are utilized to extract the lead ECG characters from the segments (**Figure 3.6**). As a final step, filters are applied to smoothen the abrupt transition between signals at the locations of character removal.

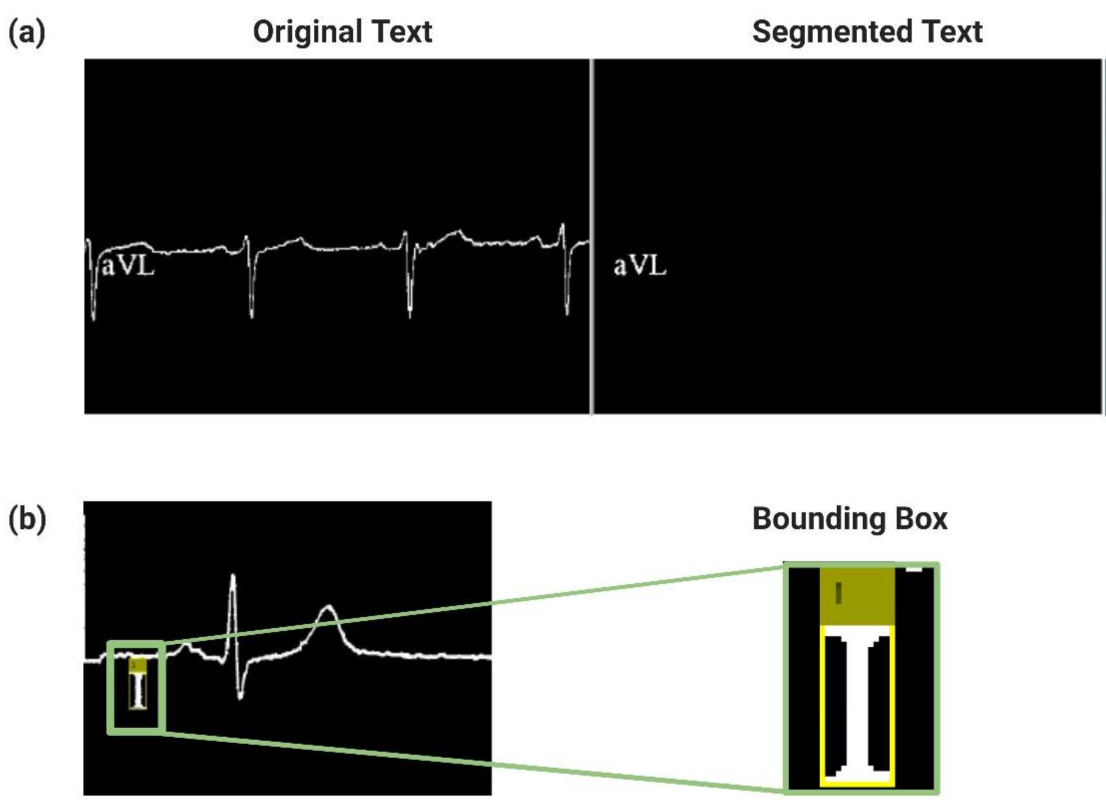

Figure 3.6 (a) The original text with the ECG lead characters (LEFT) and the segmented text with the signal removed is displayed (RIGHT). (b) The bounding box of the identified ECG lead character 'I' is depicted.

The main challenge associated with OCR is lack of access to many different varieties of ECG records. The more records available to work with, the more accurate the algorithm is. Given that data collection techniques are rapidly evolving, the availability of ECG records is bound to increase resulting in greater robustness of the algorithm. With access to increased quantity of data, the next concern would be the increase in computational time of the algorithm. However, once the template library is formed and trained with the available samples of the scanned ECG record, the process of identifying the characters followed by their removal is no longer a computationally intensive task.

Once the above 3 sections are executed, the ‘App Designer’ tool in MATLAB is used to design a GUI executing the corresponding sections in a seamless manner. The first step would be defining the user interface using a drag and drop interface, which can also be executed programmatically. Once the layout is determined, the behavior of the various component of the GUI is coded using the previously defined functions for the digitization of scanned ECG records. The code is highly modular and is hence very easy to modify for future use. A detailed instruction manual on how to train the template using OCR is provided in Appendix C.

CHAPTER 4

RESULTS

This chapter discusses the results obtained from the ECG digitization algorithm. The manual for the ECG digitization application and the manual for OCR training is available in Appendix B and Appendix C, respectively. Section 4.1 details a range of results obtained for the digitized ECG signal, extracted patient demographic information and removal of ECG lead characters using OCR. Section 4.2 delineates the results of the reader study conducted at Emory. Section 4.3 discusses the implications and relevance of the results obtained thus far.

Section 4.1 ECG Digitization and OCR Results

The ECG digitization application provides the user with the digitized ECG signals organized in a structured format corresponding to the original ECG records, along with the demographic information of the patient stored in a text document. Utilizing OCR, the characters in the "Demographic Region" were preprocessed, identified and stored in a text document (**Figure 4.1**). The intermediate results obtained during the process of digitization of a sample paper ECG record is shown in **Figure 4.2**. The final digitized ECG sample version shown here is unscaled and uncentered, which means that the scaling is still in terms of raw pixel values, and not voltage-time pairs. A few examples of accurate digitization are displayed in **Figure 4.3**, as well as inaccurate digitization in **Figure 4.4**. The underlying reasons for the variation will be discussed in extensive detail in Chapter 6.

Specific examples of the varying degrees of success of character removal of lead ECG characters is displayed in **Figure 4.5**.

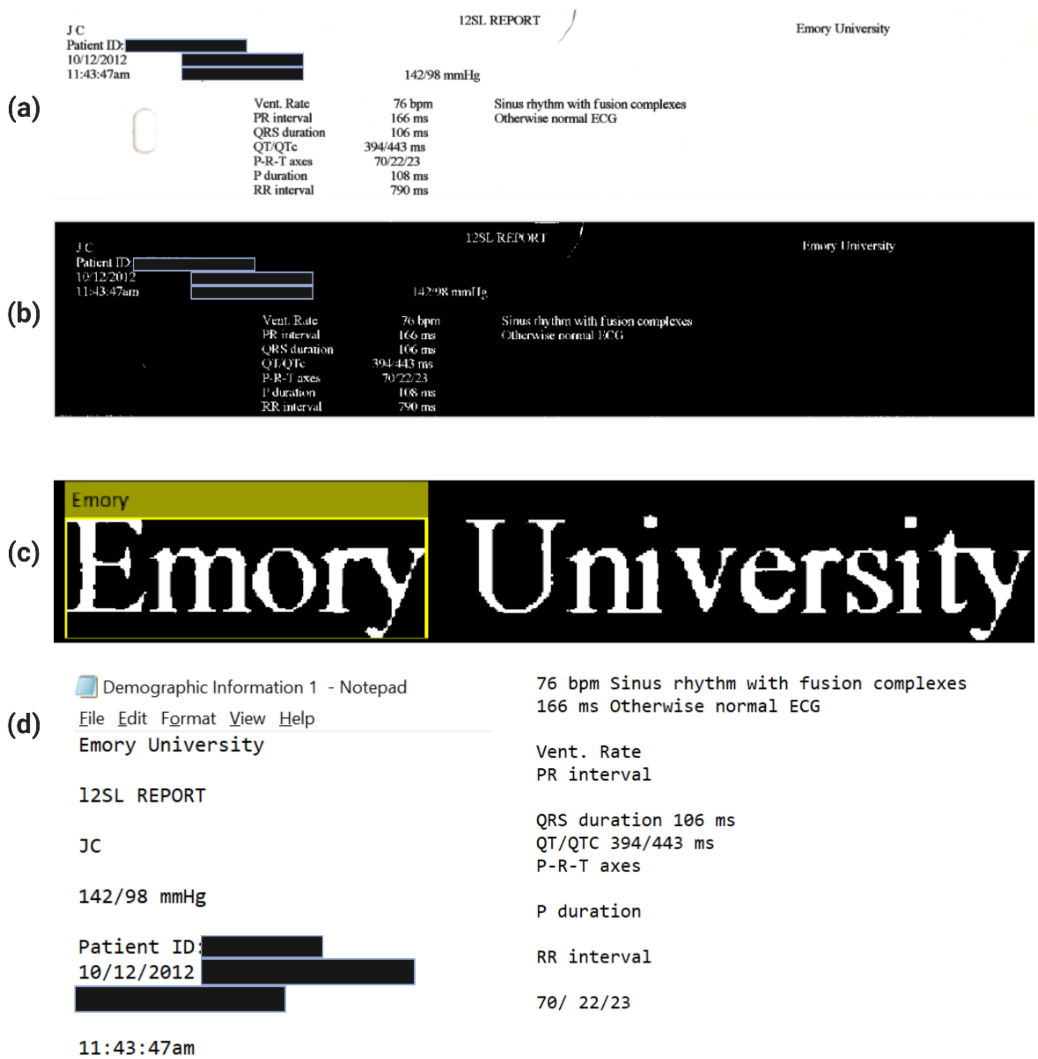

Figure 4.1 This figure showcases the intermediate steps taken to extract demographic patient information. (a) The original demographic information of the paper ECG record is displayed. (b) This portion of the ECG record is preprocessed utilizing thresholding, and morphological techniques such as erosion and dilation. (c) The OCR algorithm identifies words such as “Emory” and “University”, with an associated confidence level. If the confidence level is too low, the word will be discarded and not included in the text. (d) The textual information obtained from the paper ECG record is stored in a text document. Note, all identifying patient information has been removed.

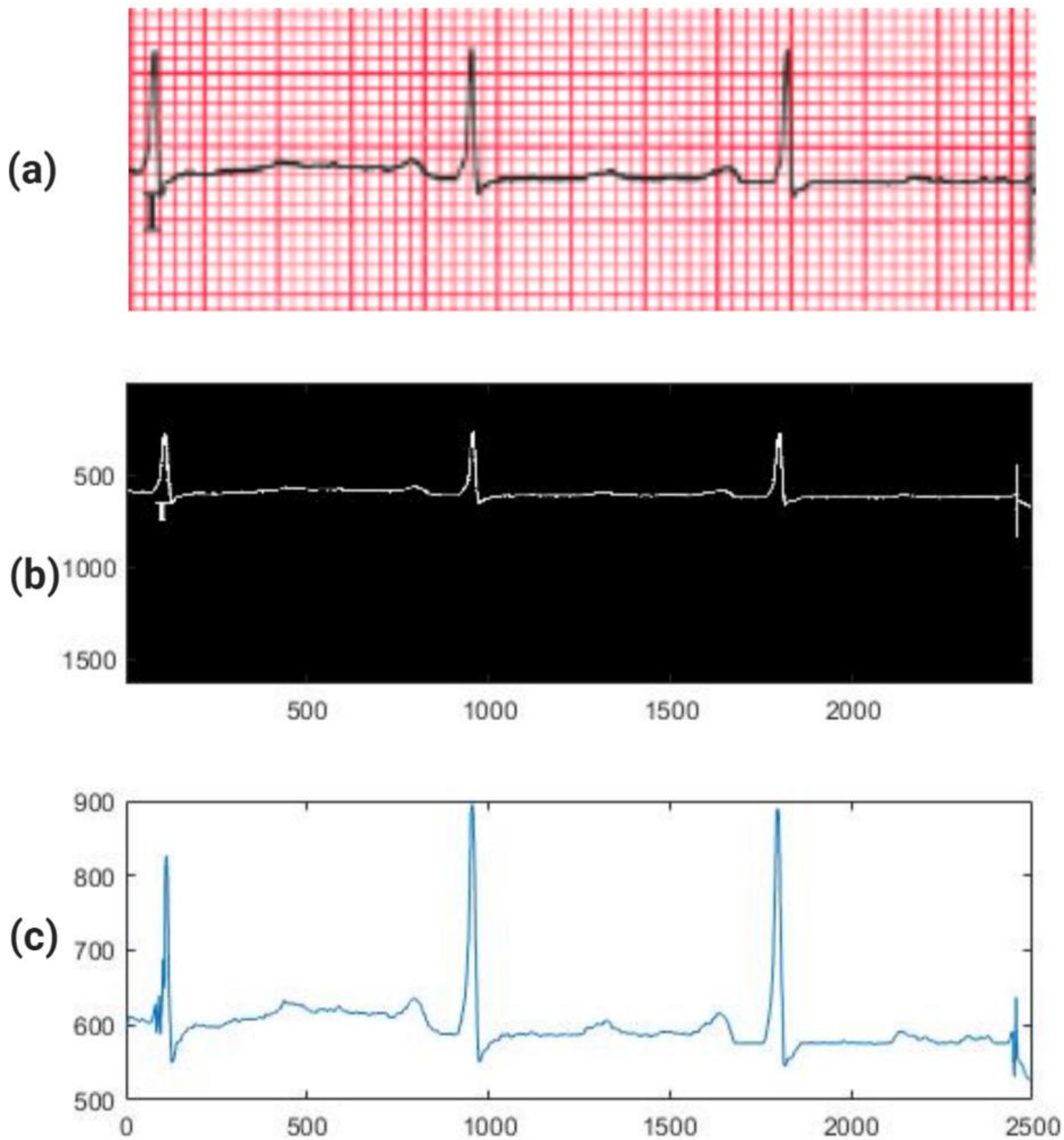

Figure 4.2 The unscaled intermediate results are shown sequentially for the ECG digitization process. (a) Sample paper ECG record with any processing is shown. (b) Image obtained after application of thresholding and filtering is displayed. (c) Unscaled and uncentered digitized ECG signal obtained.

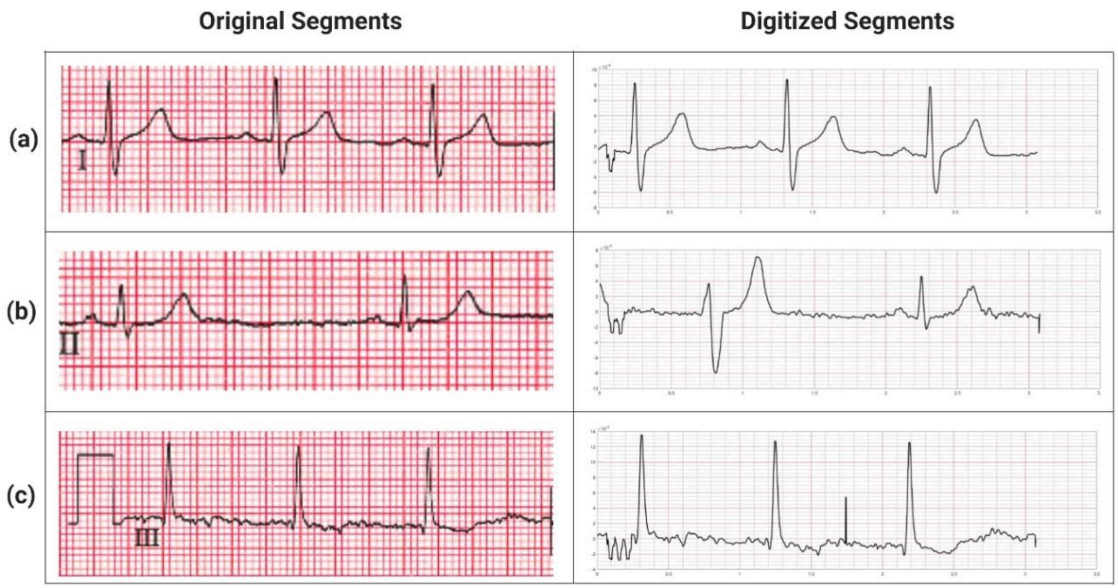

Figure 4.3 Examples of accurate digitization of the paper ECG records into digitized ECG segments.

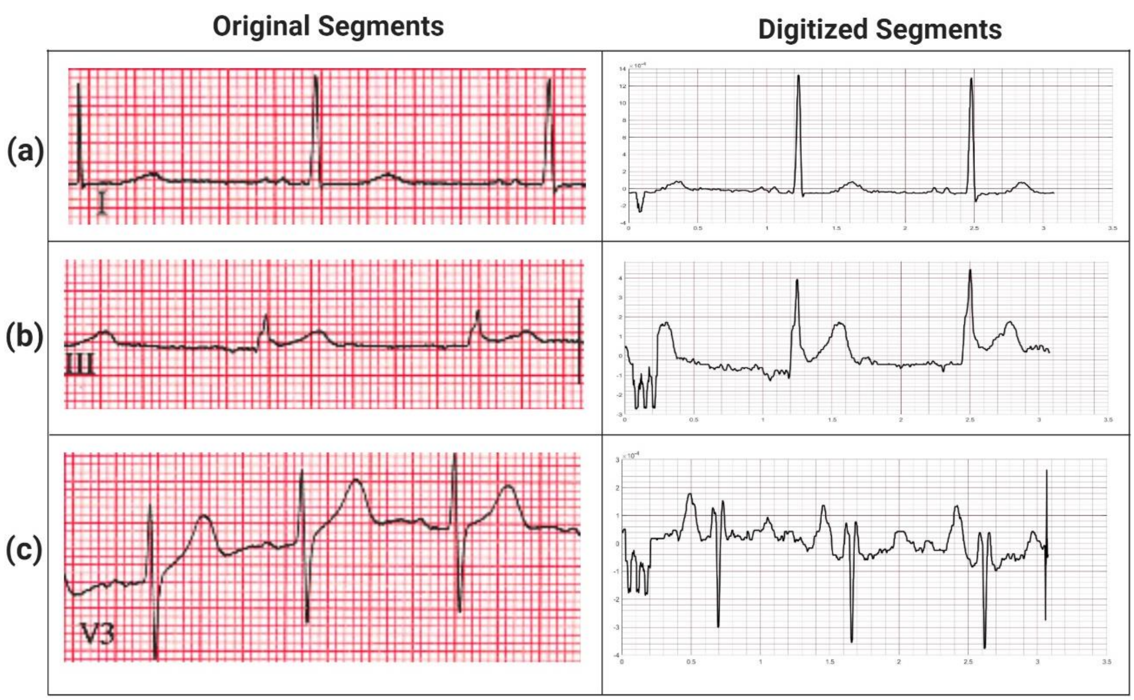

Figure 4.4 Examples of inaccurate digitization of the paper ECG records into digitized ECG segments are displayed. (a) The first ECG peak that exists in the original signal, is omitted from the digitized signal. (b) The amplitude of the peaks in the digitized signal is scaled up, but the position of the peaks along with its general shape is preserved. (c) The general shape of the digitized ECG signal is not preserved, with erratic variations seen in the amplitude of the digitized ECG signals.

Figure 4.5 Character removal instances with varying degrees of success is displayed. The border of the box in which the character is detected is referred to as the bounding box. (a) The bounding box accurately identifies the character and the character is removed. (b) The bounding box misidentifies a portion of the ECG signal to be a part of the character, which leads to partial removal of both signal and the identified character. (c) The bounding box again misidentifies a portion of the ECG signal to be a part of the character, which leads to partial removal of both signal and complete removal of the identified character. (d) The bounding box partially identifies a portion of character and removes it.

For the quantification of OCR results, the classification of the ECG segments was organized into 3 categories (**Figure 4.6**). These categories were based on the degree of identification and removal of the ECG lead characters.

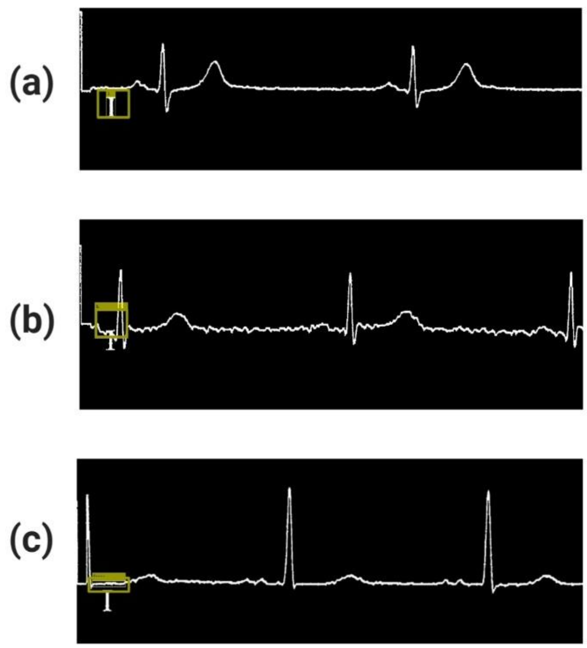

Figure 4.6 The 3 categories into which OCR results are classified into are displayed. (a) The bounding box captures the entire ECG lead character, which is category 1. (b) The bounding box captures part of the ECG lead character, and part of the ECG signal, and hence is classified into category 2. (c) The bounding box completely misses the ECG lead character and captures a part of the signal instead. This falls into category 3.

Table 4.1 Quantitative results of OCR on ECG segments

	Number of segments in test set	Percentage as a function of total segments evaluated
Category 1	313	71.298%
Category 2	85	19.362%
Category 3	41	9.339%
Total Segments Evaluated	439	

Table 4.1 gives the quantitative tabulations for the OCR evaluations performed, and the rate of selection of only characters by OCR is 71.298%, the rate of selection of both

signal and characters by OCR is 19.362% and the rate of selection of only signal by OCR is 9.339%.

Section 4.2 Validation Study Results

The validation study was carried out on 53 ECGs from the Emory Vietnam Era Twins (VET) Study [30]. The study tested 5 clinically important features of ECG signals namely the *PR* interval, *QRS* interval, *QT* interval, *RR* interval and the QT_c interval (**Figure 4.7**). The QT_c interval is formulated using the following Equation 6.1.

$$QT_C = \frac{QT}{\sqrt{RR}} \quad (6.1)$$

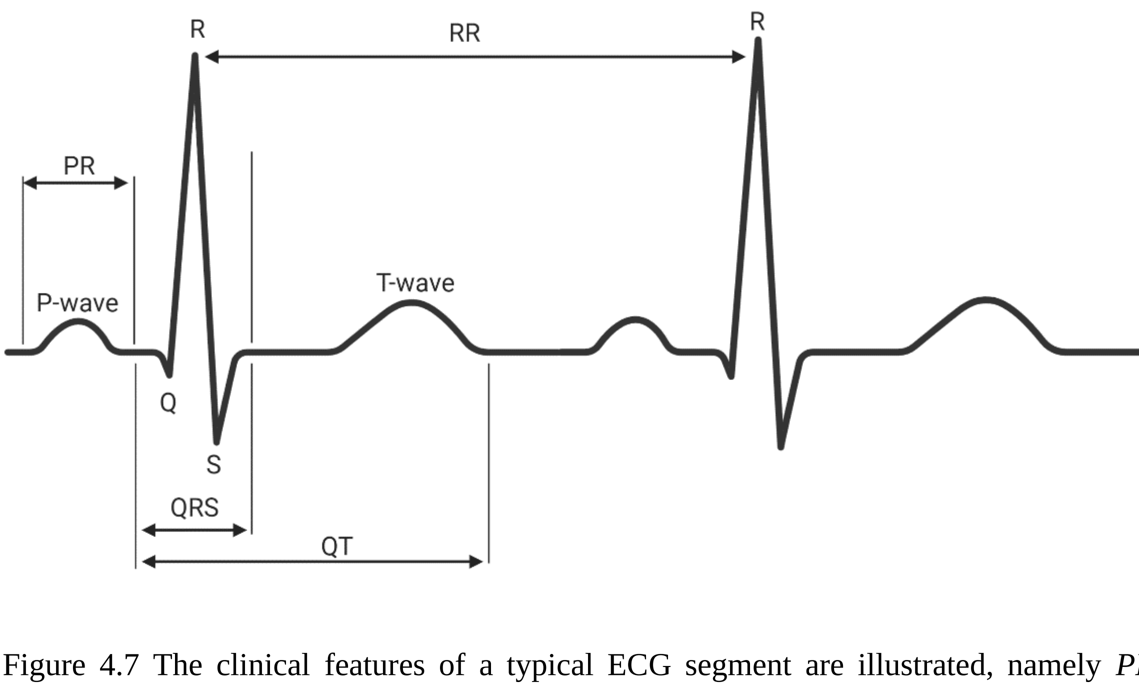

Figure 4.7 The clinical features of a typical ECG segment are illustrated, namely *PR* interval, *QRS* interval, *QT* interval and *RR* interval.

Based on the values obtained from the digitized ECG records, the kappa statistic [31] was calculated as a measure of the level of agreement. The study was carried out by two cardiology readers at Emory to calculate the intra-observer and the inter-observer measurements for the 10 randomly selected ECG records. Cardiology reader 1 and cardiology reader 2 measured five parameters from the paper ECG records and the digitized ECG records, between which there was a 24-hour washout period. In order to calculate the inter-observer statistics, cardiology reader 2 measured the 5 parameters for the first 5 ECG scanned records and last 5 ECG digitized records. These measures were compared to those of cardiology reader 1 obtained in the exact opposite manner. Of the five parameters measured, three were used for calculation of the intra-observer and inter-observer correlation measurements, namely *RR* interval, *QT* interval and QT_c interval. The raw measurements for two parameters *QRS* and *PR* intervals were not directly available, instead those measurements for which *QRS*>120 ms (intra-ventricular conduction delay) and *PR*>120 ms (first-degree atrioventricular block) were taken into consideration.

Table 4.2

Correlations calculated from the measurements obtained by the cardiology readers

Parameter	Correlation Coefficient, intra-observer 1	p-value	Correlation Coefficient, intra-observer 2	p-value	Correlation Coefficient, inter-observer	p-value
RR	0.9153	0.0002 ($p<0.001$)	0.9371	0.0000634 ($p<0.001$)	0.9108	0.0002 ($p<0.001$)
QT	0.2557	0.4758 ($p>0.001$)	0.5971	0.0684 ($p>0.001$)	0.6186	0.0566 ($p>0.001$)
QT_c	0.4294	0.2056 ($p>0.001$)	0.3738	0.2872 ($p>0.001$)	0.5861	0.075 ($p>0.001$)

Table 4.2 contains the intra-observer 1 correlations, intra-observer 2 correlations and the inter-observer correlations computed from the measurements obtained by the two cardiology readers. The intra-observer correlation coefficients for the *QT* interval, QT_c interval and *RR* interval ranges, for both cardiology reader 1 and cardiology reader 2 ranges from 0.2557 to 0.9371. The *RR* intervals computed are statistically significant ($p<0.001$), although *QT* and QT_c intervals are not found to be statistically significant ($p>0.001$).

The inter-observer correlation coefficients for the *QT* interval, QT_c interval and *RR* interval ranges, for both cardiology reader 1 and cardiology reader 2 ranges from 0.5861 to 0.9108. The *RR* intervals computed are statistically significant ($p<0.001$), although *QT* and QT_c intervals are not found to be statistically significant ($p>0.001$). The kappa statistic ranges between -0.4886 to 0.8742, for the intra-observer measurements. For the inter-observer measurements, the kappa statistic ranges between 0.1722 and 0.8216.

Section 4.3 Discussion and Conclusions

The aim of the current algorithm was to primarily extract the ECG signals in a digitized format from the scanned ECG records. From the clinical study conducted, it can be concluded that the algorithm implemented with its present form of methodology is not suitable for digitization of ECG records, due to its inconsistent nature of results.

The lower correlation coefficient values, along with the corresponding kappa values can be attributed to a possible scaling issue. It can be observed that the raw values of the *RR* and *QT* intervals obtained from the digitized ECG signals are offset consistently by a range of 160-400 ms and 10-150 ms respectively, when compared with the intervals measured from the paper ECG segments. The *RR* intervals although offset, still have high correlation values associated with it, 0.91-0.93. This suggests that during the process of reformatting the digitized ECG signal into a grid format for the purpose of the clinical study, a possible offset could have been introduced.

It is also possible that residual ECG lead characters, or overextension of ECG signals from adjacent segments due to improper segmentation may have resulted in further distortion of the extracted digitized ECG signal. The potential reasons for the low correlation and kappa values are further detailed in Chapter 5, in which the limitations of the current methodology are explored. Despite the inconsistent results, this body of work is still promising and has the potential to pave the way for better results in the future. Using this type of open source ECG digitization tool, it is possible to carry out retrospective analysis on existing paper ECG records. It can also be used to further integrate ECG signal information with that of the patients EMR information.

CHAPTER 5

LIMITATIONS AND FUTURE WORK

This chapter delves into the limitations posed by the proposed algorithm for digitization of ECG signals and potential future work that can be built upon the proposed algorithm. Section 5.1 deals with the limitations of the methodology designed and tested for the digitization of paper ECG records. Section 5.2 investigates the possible future works that can be derived from the current algorithm.

Section 5.1 Limitations

Although the results of the proposed ECG digitization algorithm and the reader study were promising, certain segments of the scanned ECG records were found to be inaccurately digitized. The reader study results revealed that there is room for improvement in the algorithm since some of the parameters measured were not faithfully reproduced by the ECG digitization application. The limitations of the current methodology will be elucidated over the following paragraphs.

The current methodology heavily relies on the user defined parameters for each type of ECG record. Consequently, the extent to which the scanned ECG records are digitized depends on the accuracy of these parameters stored in the algorithm. Given the specific coordinates of the DC pulse as a parameter, the algorithm partitions all the ECG leads in a single scanned record. There are instances where the rigid segmentation does not entirely capture a single ECG signal in a segment (**Figure 5.1**). Certain ECG signals can overextend into the adjacent segments, due to anomalous cardiac behavior. During the process of column wise pixel scanning in order to extract the digitized ECG signal, the anomalous ECG segments skew the digitized values. In turn, this contributes to a decrease in robustness of the algorithm.

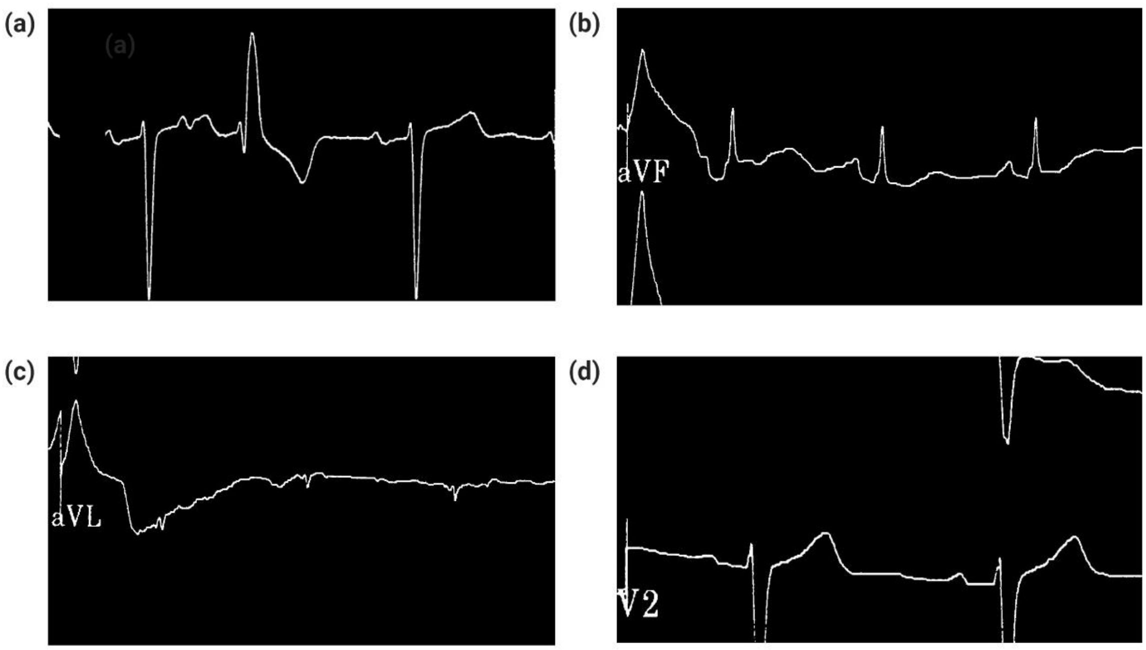

Figure 5.1 Anomalous cardiac behavior often causes overextension of the peaks of the ECG signals in the scanned ECG records. The scanned ECG records are subjected to thresholding and grid removal. (a) The digitization in the current segment will not be affected, but since the peaks in the current segment extend below into the adjacent segment, the same cannot be said of it. (b) The main ECG signal in this segment is preserved, but a large peak from the segment below will likely cause skews in the digitization of the main ECG signal. (c) The digitization of the main ECG signal will be preserved for the most part, as only the amplitude of the ECG peak due to the extra ECG signal will change. (c) The digitization of the main ECG signal will be skewed, due to large peak from the segment below.

The column-wise pixel scan method is sensitive to outliers, as there is no mechanism in place to consider the overextended ECG signals. Overextended ECG signals refers to those signals that intrude from the segments above or below the present segment. The ECG leads at the bottom portion of an ECG record are affected more than others in a few cases, due to characters at the bottom of an ECG records intentionally included in the analysis of a segment (**Figure 5.2**). Although the template for a specific ECG record type is designed to capture only ECG signals, certain characters may slip in sometimes. This is due to the pre-defined template-based segmentation boundaries. In order to enhance processing speed, the pre-defined template is applied across all the ECG records in a batch. If there is a shift in the scanned record in the vertical direction, characters may be unintentionally included in the rest of the analysis.

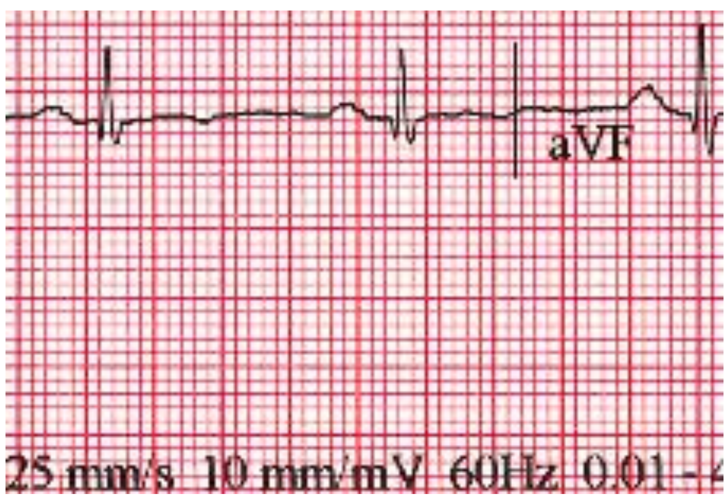

Figure 5.2 The characters at the bottom of an ECG records may unintentionally be included in the analysis of a segment.

Moving on to the OCR function, the OCR analysis is largely dependent on creating a template library utilizing the available records. Since only a small number of records were available, the training set was not extensive. Consequently, many characters were misidentified or sometimes not categorized as text. Other issues faced included merging of characters, and erosion of the characters due to extensive morphological processing (**Figure 5.3**). Another consideration is that the current OCR analysis is not optimized for handwritten text, which is seen to appear on a semi-regular basis on the paper ECG records. This will lead to loss of patient demographic information. However, there are existing packages that implement handwriting detection with OCR that have the potential to improve results.

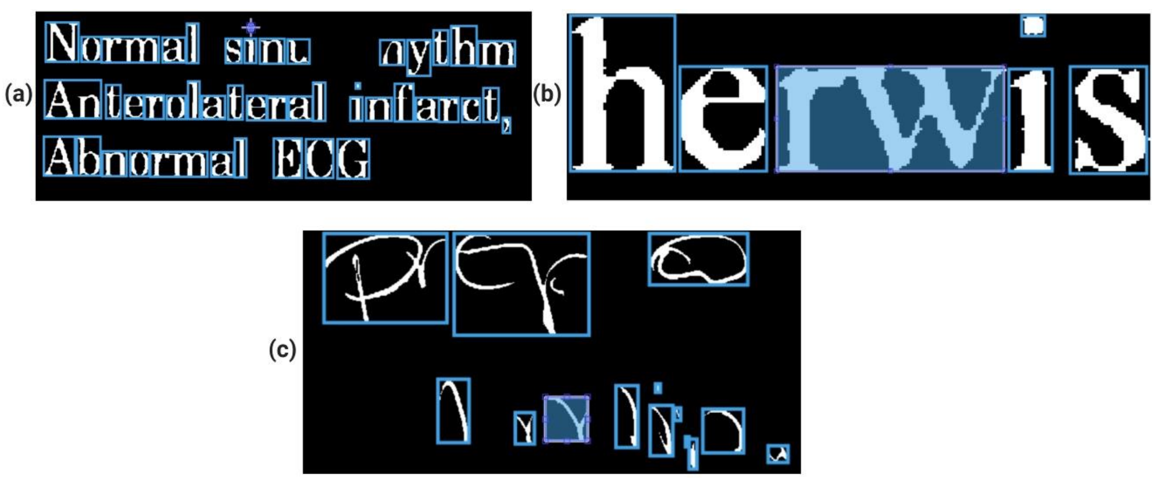

Figure 5.3 Instances in which difficulty of identification of characters arise. (a) The symbols “u” and “n” are eroded due to extensive morphological processing. (b) Characters “r” and “w” are connected. (c) Handwritten characters after processing are not picked upon and are categorized as non-text objects.

Section 5.2 Future work

With respect to future work, there are several different tests and adaptions of the algorithm that appear promising, which were beyond the timeline for the MS thesis but are important to discuss.

To begin with, an automatic ECG lead detection may result in significantly better results. Since user defined parameters have a large margin of error which propagates across other stages of the algorithm, detecting ECG leads automatically may contribute to the robustness of the algorithm. This would also lead to a decrease in user interaction, which would be beneficial in the long run. Moreover, automatic lead detection would remove the necessity for partitioning of every individual lead segment. So instead of considering the ECG signal on a segment by segment basis, an entire row of ECG signal would be considered. This could circumvent the complications associated with rigid segmentation, and a single row of ECG segments can be potentially extracted without any discontinuities.

Another consideration is complications that arose in relation to the extraction of ECG signals using column-wise pixel scan. This was also in part due to propagation of errors caused by the user defined template parameters. It may be possible to overcome these problems utilizing an algorithm called connected-component analysis (CCA) in addition to the existing column wise pixel scan, to make it more robust [32]. CCA is often used in image processing to detect connected regions in binary images. The connected regions in the current problem statement would be the ECG lead signal of interest. The implementation of this algorithm could detect, and consequently remove signals not belonging to the main ECG signal of interest in the template based segmented regions. This could help improve the accuracy of the digitized signal. Barring the cost of computational complexity, utilization of two algorithms to verify the robustness could be useful.

Focusing on the OCR algorithm, it seemed to work better for the extraction of the "Demographic region", as compared to the removal of ECG lead characters. The text characters in the "Demographic region" are admittedly more structured, so it is reasonable to expect this outcome. Apart from increasing the size of the training set by including more characters, it is helpful designate zones in which the ECG lead characters occur. This has been implemented in the current algorithm, but in the event the designated areas are too wide or too small, the characters can potentially be missed, and parts of the signal can be removed. In order to circumvent this, different scales of the region of interest can be applied to maximize the probability of detecting the ECG lead characters.

The suggestions elucidated in the above paragraphs could help improve the accuracy of the digitization of the scanned ECG records using the existing algorithm.

APPENDIX A

LITERATURE REVIEW TABLE

Table A.1

Literature Review Table

Type of ECG records used in Study	Year	Sample Size	Novelty	Software	Results	Validation	Limitation	Application Availability	Reference
VET Registry Data from the Department of Veteran Affairs	2013	53 ECGs	Optical character recognition is utilized for the extraction of patient demographic information. Batch processing is also implemented.	MATLAB	The metrics were as follows: Kappa, signal fit and correlation were >85%, 75-80% and 85-90% respectively. The intra-observer and intra-observer correlations ae 80-100%.	A blind study with 2 readers was conducted, and there were 3 types of validation tests. PR, QRS, RR, QT and QTc intervals were measured and validated used correlation and kappa statistics.	The signal fit was only 75-80%, which is a lower fit compared to other studies. Does not address the issue of overlapping lead characters of the ECG signals, as well as the intersection of ECG leads.	No	[7]
Not Mentioned	2013	Not Mentioned	The data is extracted from ECGs stored as a pdf format. The pixel coordinates of the ECG data points in the pdf are used to reconstruct the ECG signals.	MATLAB	Depending on the template of ECG records used, the time for extraction rages from 3-13 seconds per ECG record. Screenshots of GUI presented along with digitized signal presented as results.	No specific method mentioned.	Designed only for ECG records stored as pdfs/Support Vector Graphics. Does not work on scanned ECG records.	Yes, available as a standalone GUI. (open source)	[26]
Not Mentioned	2015	Not mentioned	Addresses the problem of multiple intensity points detected while implementing vertical scan to extract ECG signal. It is proposed that the highest intensity point in a column be considered the point on the curve of the ECG signal.	Not Mentioned	No Quantification of results, only pictures and screenshots of results presented.	No specific method mentioned.	Does not address the issue of overlapping characters on the ECG signals.	No	[29]
PTB, MIT-BIH	2016	Not mentioned	Proposed removal of background grid in ECG signal, by initially calibrating the axes of the ECG segment, and then storing the x-y coordinates of the ECG signal.	MATLAB	No Quantification of results, only pictures and screenshots of results presented.	No specific method mentioned.	Requires excessive amounts of user input. Does not address the issue of overlapping characters on the ECG signals.	Yes (not open source)	[22]

Table A.1

Literature Review Table (Continued)

Type of ECG records used in Study	Year	Sample Size	Novelty	Software	Results	Validation	Limitation	Application Availability	Reference
Mini-Finland Heath Survey (1978-1980)	2017	6963	Digitization of ECG records carried out by trained personnel. A new application was developed with tailored manual tools for ECG signal extraction. ECG lead intersection was tackled manually. Demonstrates large scale robust conversion of ECG records.	MATLAB, SPSS	The mean inter-method differences ranged from – 4.3 ms to 5.4 ms for PR interval, from – 3.3 ms to 0.3 ms for QRS duration, and from 4.1 ms to 18.6 ms for QT interval. The kappa-values for PR intervals, QRS duration and QTc intervals were 0.83, 0.72 and 0.33 respectively.	100 ECGs randomly sampled. An examiner blinded to the selection of ECG measured and compared PR, QRS and QT interval along with heart rate, R wave amplitude, S wave amplitude and T wave amplitude. The inter-method agreement of abnormal intervals was analyzed using Cohen's kappa coefficient and McNemar's test.	Each ECG record must be digitized manually. Does not address the issue of overlapping characters on the ECG signals.	Yes, available as a standalone GUI. (not open source)	[23]
Records obtained from "Various diagnostic centers". Not specified.	2018	836	Entropy bit-plane slicing method proposed, in order to extract the bit plane containing the highest signal to noise components in the degraded ECG signals. Degradation involves variable ECG paper color, faded ink, and folded paper.	MATLAB	The accuracy, sensitivity and specificity of the method is 99.42%.99.69% and 99.91%. The F-measure of ECG is 99.26%. The RMS error and correlation for 101 cases is 0.040 and 99.89% respectively.	101 digitized ECG records compared with the paper ECG outputs directly form the machines. The rms error, degradation parameter and correlation are measured.	Does not address the issue of overlapping lead characters of the ECG signals, as well as the intersection of ECG leads.	No	[15]
Tertiary Teaching Hospital in Korea (23-year study period)	2018	1039550	Designed only for ECG records stored as pdfs/Support Vector Graphics. Does not work on scanned ECG records	JAVA, Python	99.94% accuracy of QTc value within +/-2ms.	No specific method mentioned.	Designed only for ECG records stored as pdfs/Support Vector Graphics. Does not work on images of scanned ECG records	Codes available. (open source)	[25]

Table A.1

Literature Review Table (Continued)

Type of ECG records used in Study	Year	Sample Size	Novelty	Software	Results	Validation	Limitation	Application Availability	Reference
Not Mentioned.	2019	129	The proposed method implements Connected Component Analysis to extract the ECG signals from the background grid. The algorithm proposes to extract 12 ECG lead segments simultaneously.	MATLAB	The average root mean square error is 2.23% and the percent mean square error is 3.34% for the RR intervals measured for the 7 ECG records.	The R-R interval of 7 ECGs was manually measured and compared. It is quantitatively measured by root mean square and percent mean square error.	Does not address the issue of overlapping lead characters of the ECG signals, as well as the intersection of ECG leads. It is also not robust enough as only the RR interval was measured.	No	[21]
American University of Beirut Medical Center	2019	30	The proposed method is applicable to ECG records of any resolution and not limited to 300 DPI or 600 DPI. The paper also claims automatic lead detection to be implemented for the first time in literature.	MATLAB	The correlation values of PR interval obtained is 0.984(p-value < 0.001), QRS interval 1 (p-value < 0.001), QT interval 0.981 (p-value <0.001), and RR interval (p-value <0.001.)	The validation of the results was performed with each signal having a 1000 data-points interval and constituting of a minimum of 4 heartbeats. The signals were printed and afterwards scanned.	This is not applicable to ECG templates with more than 12 leads. Batch processing of ECG records are also not possible. They have not addressed overlapping of lead characters on the ECG signals. There was no clinical study to performed during validation.	Yes (Not open Source)	[20]

APPENDIX B

ECG DIGITIZATION APPLICATION MANUAL

Section 1

Installation of ECG App

This section details the instructions for installing the application, ‘ECG App’, which is designed for the digitization of the scanned ECG records. The application is designed on ‘App Designer’ on MATLAB. The rest of Appendix B contains instructions in the form of figures, and text interspersed wherever necessary.

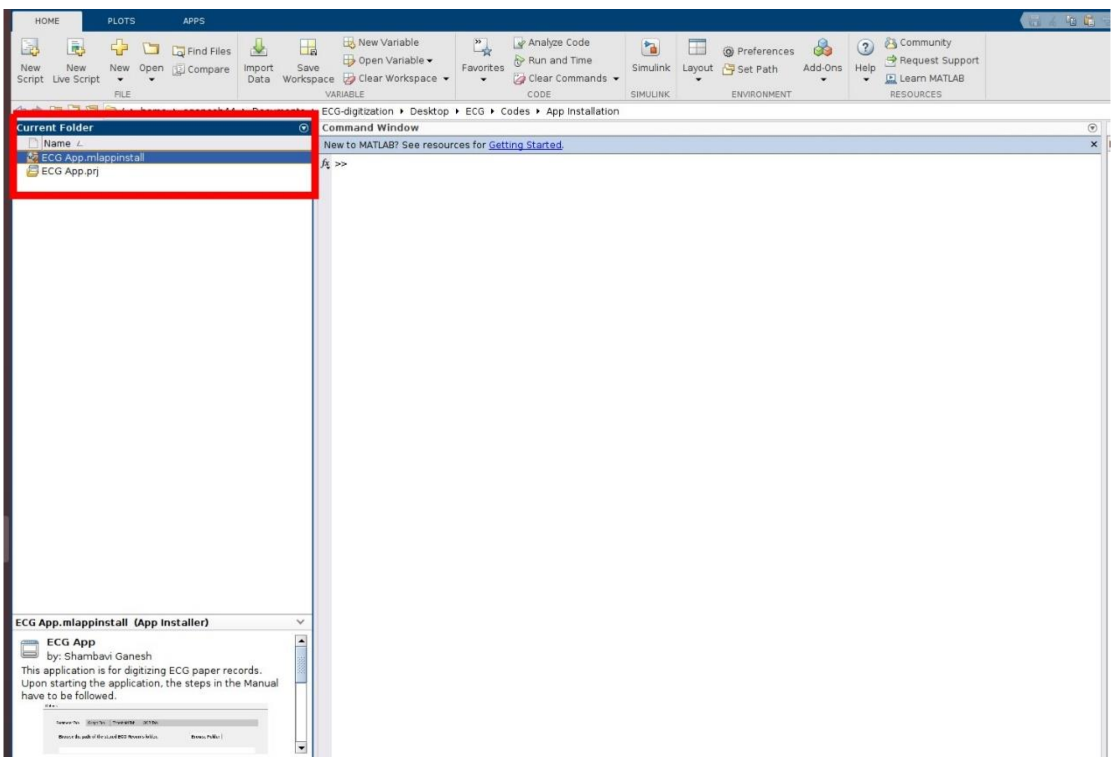

Figure B.1 The application can be opened by first extracting the zip file “ECG APP” into a folder. The file runs on MATLAB, so it is necessary to have MATLAB (preferably 2014a or above) open. In MATLAB, navigate to the “ECG APP” folder, in the current folder window. Double click on “ECG App.mlappinstall” in the window, to install it.

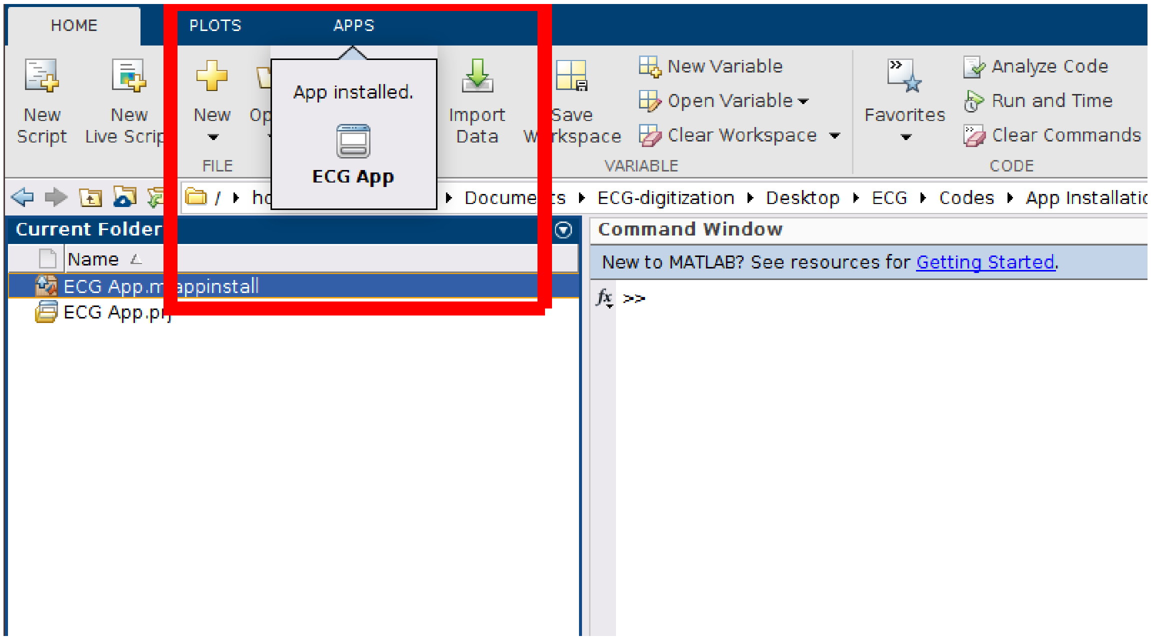

Figure B.2 Once the app is installed, it will be clearly indicated in the "APPS" tab of MATLAB, with "App installed" being displayed.

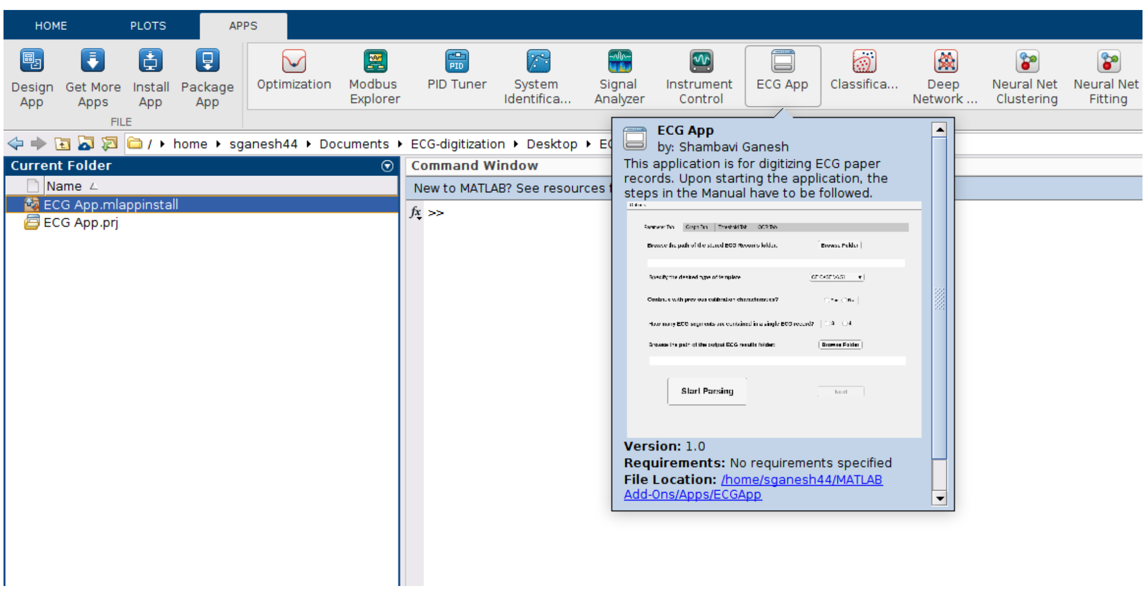

Figure B.3 Click on the "APPS" tab, and the ECG App icon should be visible under the APPS tab. Double click on the ECG APP icon.

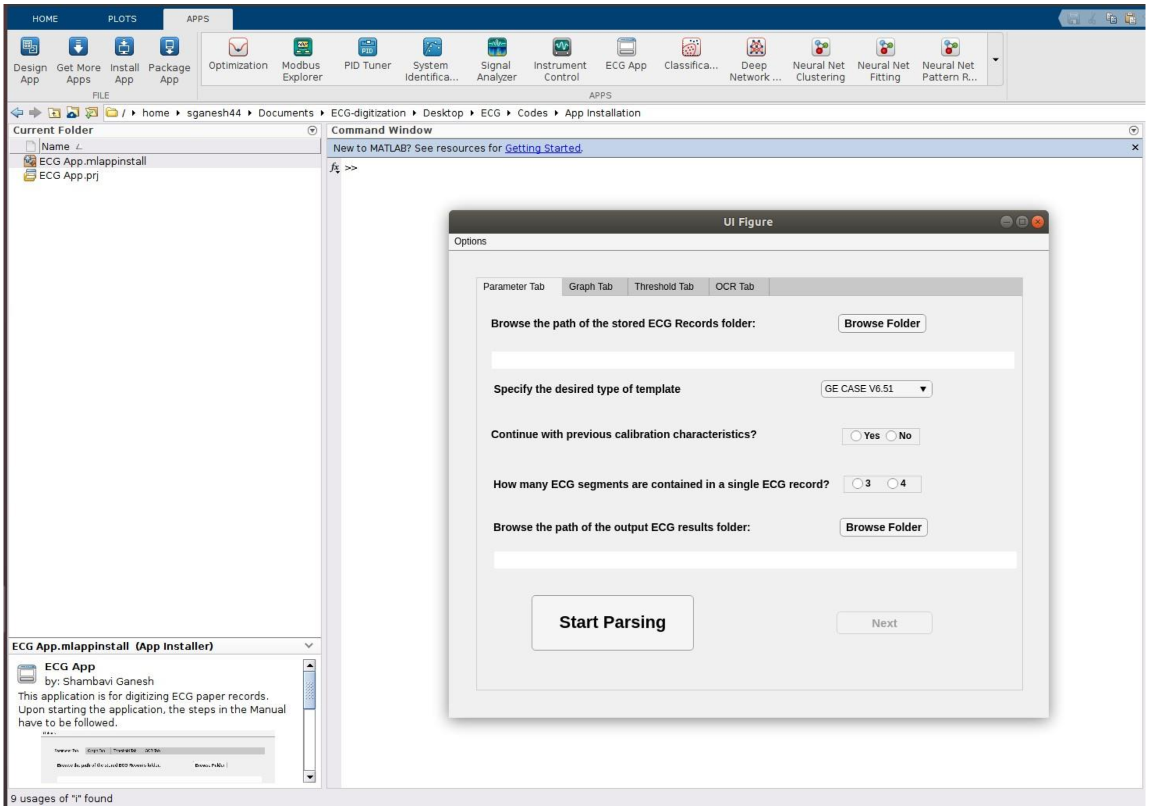

Figure B.4 The ECG App will open, and the initial tab, “Parameter application” will be displayed.

Section 2

Brief Introduction to the Tab Groups

There are 4 tabs groups in the ECG APP, namely the Parameter Tab, Graph Tab, Threshold Tab and OCR Tab. There is no need to navigate between the tabs, as there are "Next" buttons in each Tab which takes the user to the appropriate next step. The function of each of the tabs are explained as follows:

1. **Parameter Tab:** This tab requires information about where files are stored, and the type of ECG record being processed.
2. **Graph Tab:** This tab needs to be accessed to provide further information about the template and parameter information, in case the user desires it. This Tab need not be accessed during every iteration.
3. **Threshold Tab:** This tab lets the user decide the appropriate threshold value for a set of ECG records.
4. **OCR Tab:** This tab merely asks the user whether character removal from the records are desired.

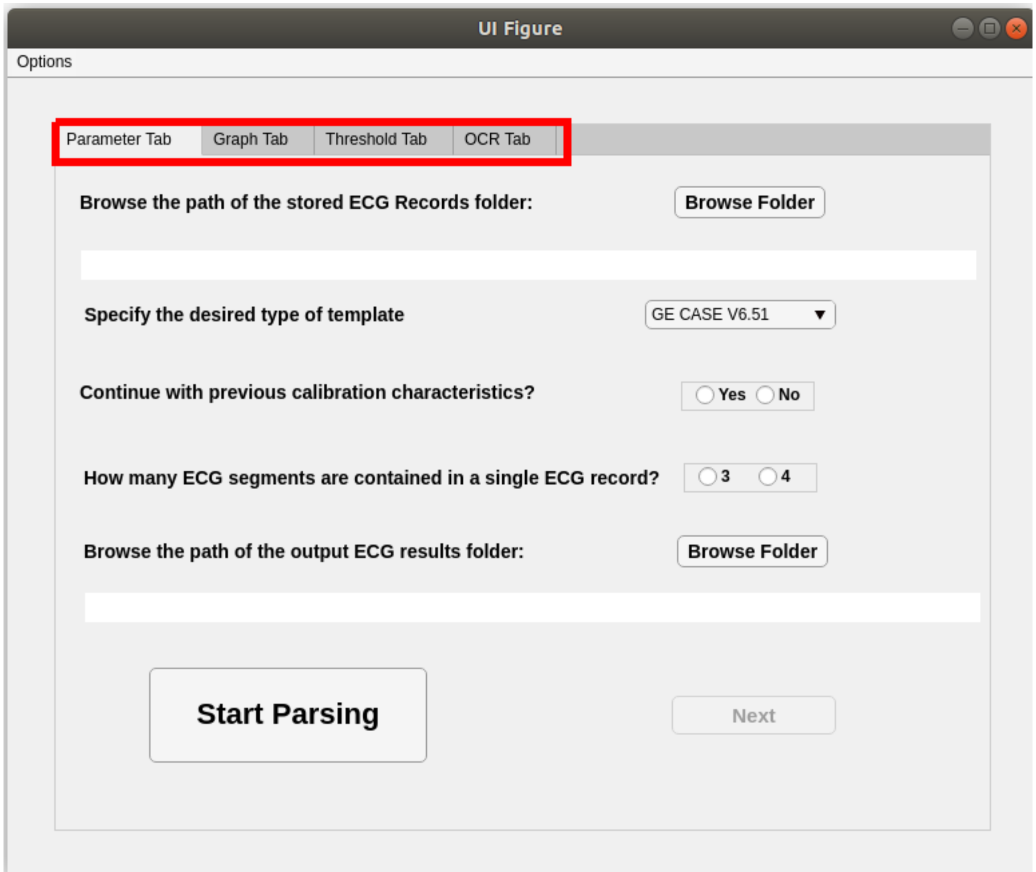

Figure B.5 The Parameter Tab, Graph Tab, Threshold Tab and OCR Tab of the ECG App are displayed.

Section 3
Navigating the Tabs Parameter Tabs

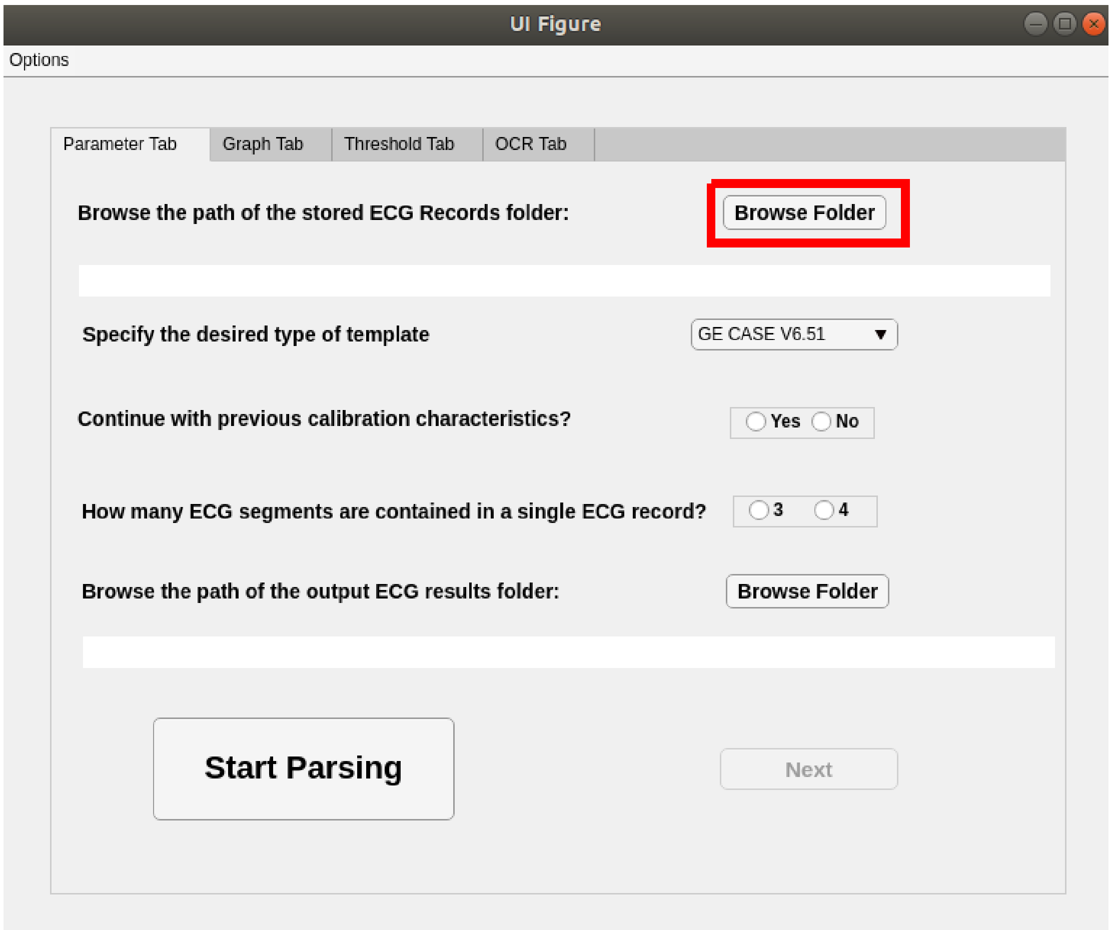

Figure B.6 The folder path to the stored ECG scanned files must be specified, by pressing the ‘Browse Folder’ in the Parameter Tab.

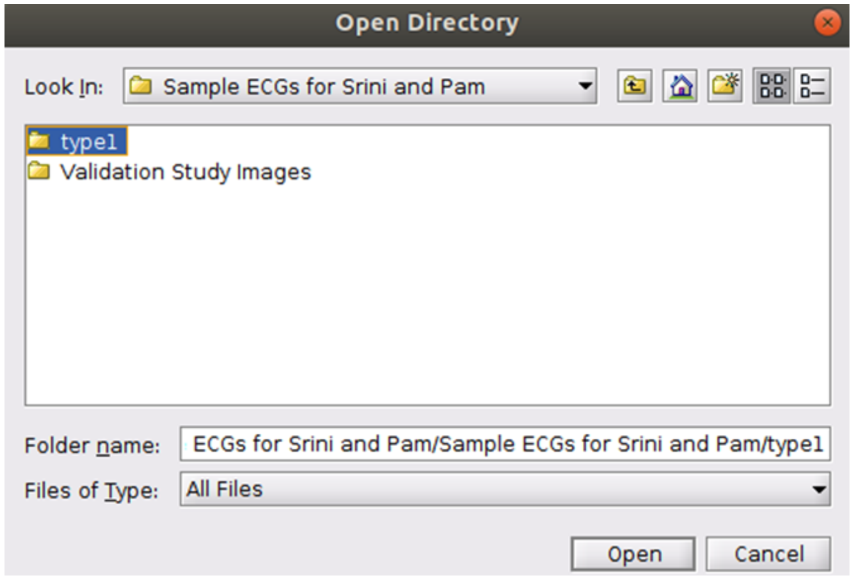

Figure B.7 A pop-up window appears. The folder in which the scanned ECG records are stored, must be selected. Please make sure only the pictures (of any valid format) exist in this folder and nothing else.

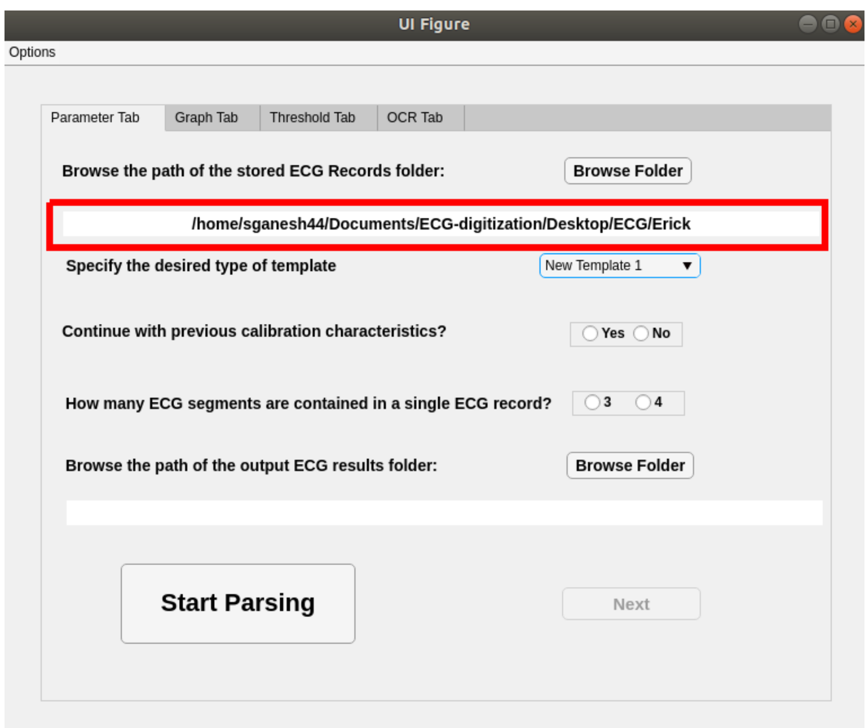

Figure B.8 Path of the folder selected will appear in the space highlighted, which the user can cross verify.

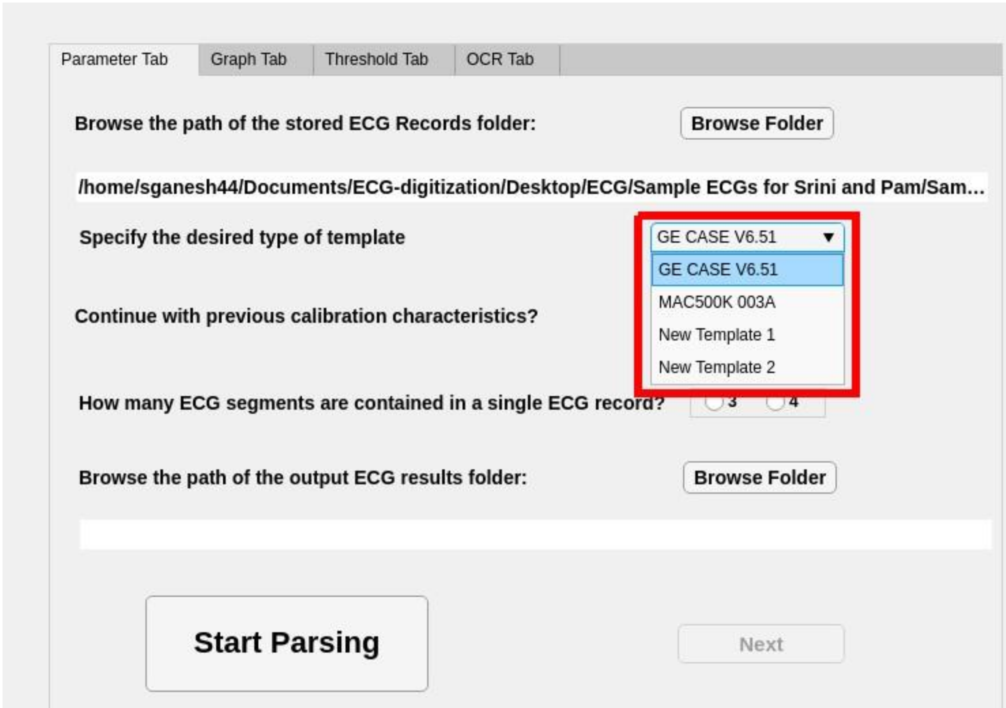

Figure B.9 The template of the ECG record needs to be selected, corresponding to an ECG machine. If the present ECG records do not match available options (GE CASE V6.51 or MAC500K 003A), then the user can store the new parameters by selecting “New Template 1” or “New Template 2”.

Calibration parameters can be loaded by selecting “YES”, or the user can choose to create new calibration parameters by selecting “NO”. If the user is selecting “New Template 1” or “New Template 2”, please make sure to choose “NO” so that the new parameters of the template can be stored. It is recommended that when the user is using the set of records for the first time, option “NO” should be chosen. If the user wishes to select option “YES”, please continue reading on page 48 (**Figure B.10**). If the user wants to select option “NO”, please move onto page 52 in this section (**Figure B.17**).

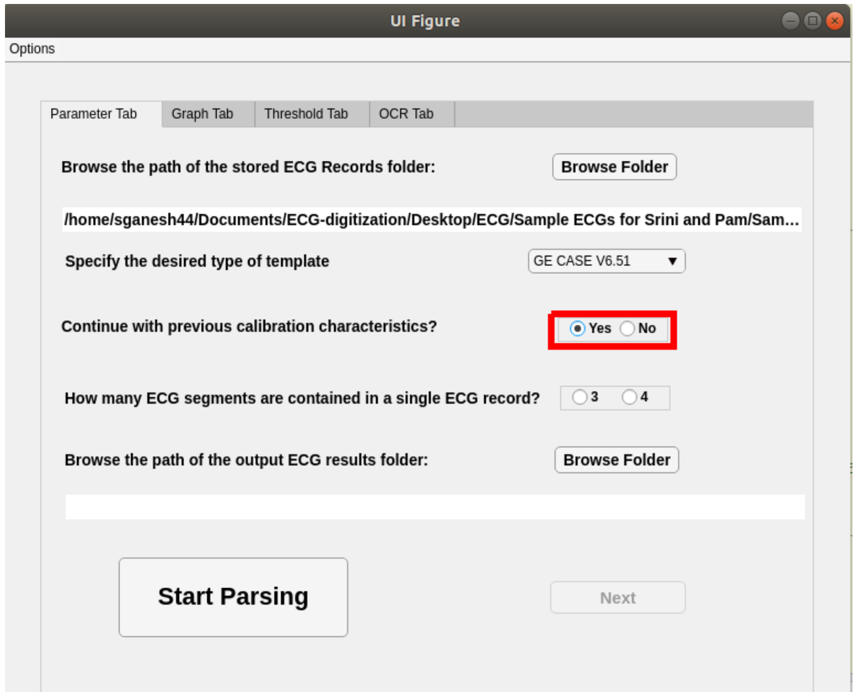

Figure B.10 The user can choose “Yes” or “No” options, with respect to whether they want to include previous calibration characters.

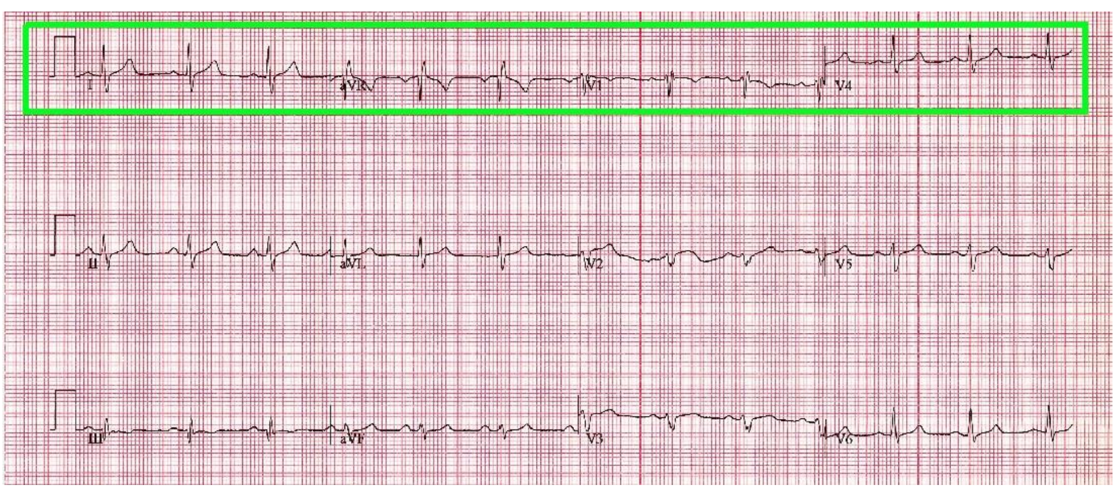

Figure B.11 An example of an ECG segment is highlighted, which corresponds to a row in the ECG record.

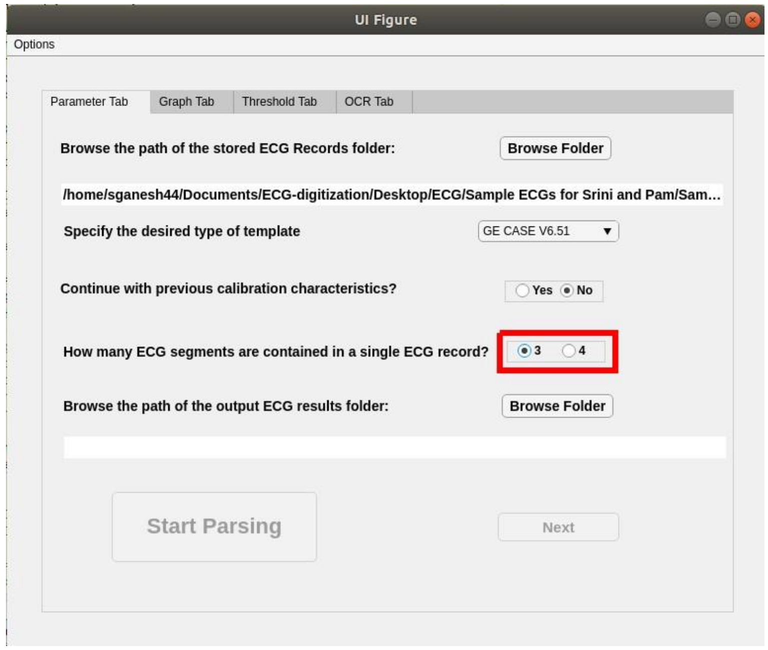

Figure B.12 The number of segments chosen in this example is 3, for that subset of ECG records.

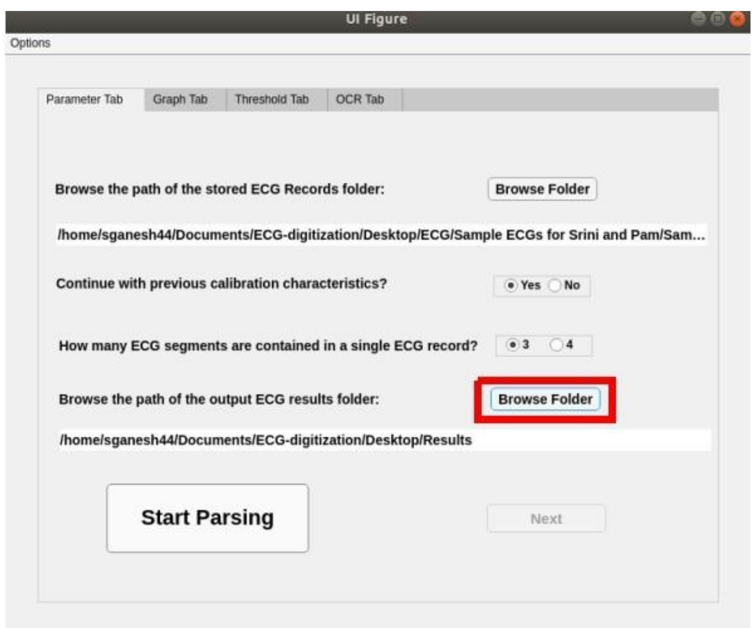

Figure B.13 The output folder in which the results are to be stored, needs to be selected via the ‘Browse Folder’ option.

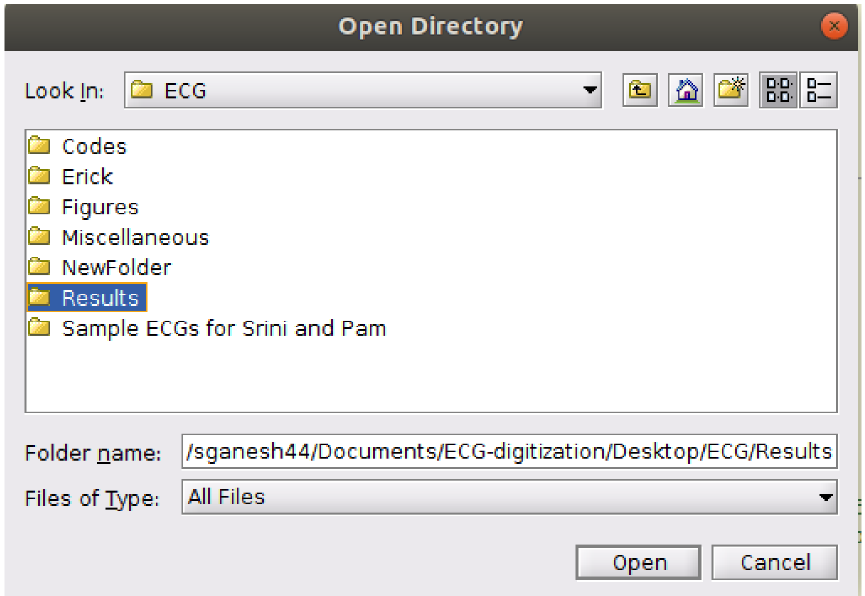

Figure B.14 Upon selecting the 'Browse Folder' option, a pop-up window will appear.

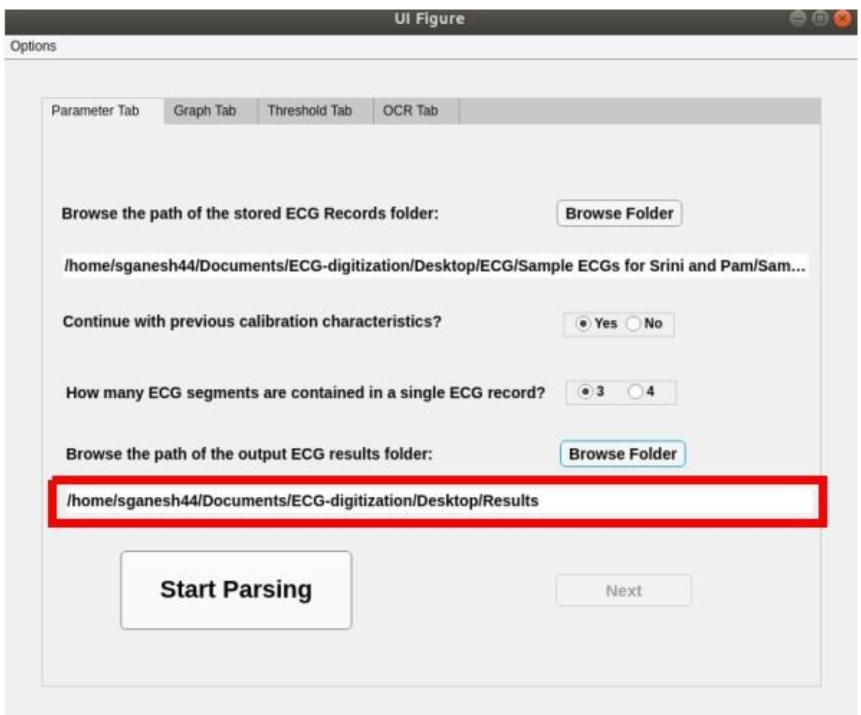

Figure B.15 The path of the output folder selected can be verified in the space highlighted.

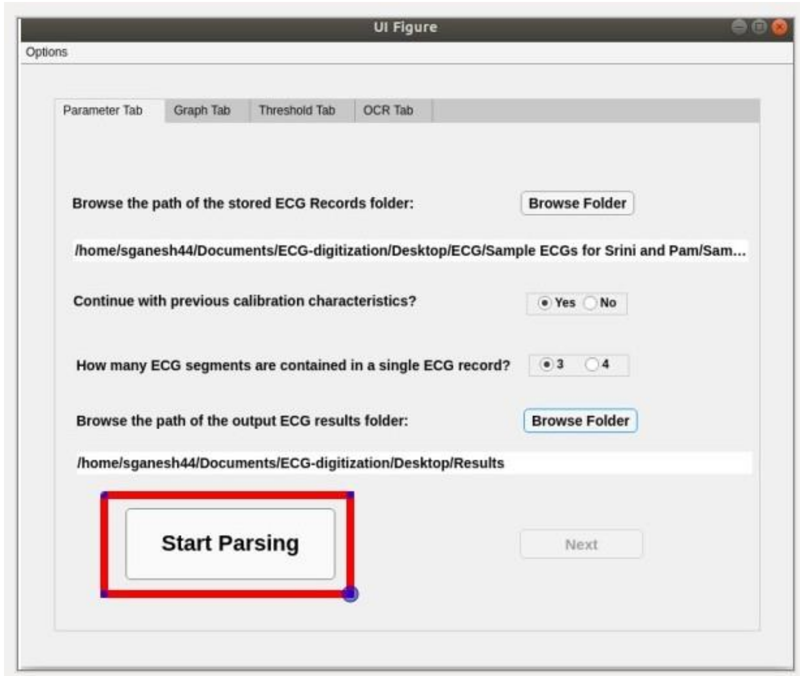

Figure B.16 The “Start Parsing” button that is highlighted, needs to be selected in order to start calibration of the ECG records.

A pop-up window denoting the progress of calibration will be displayed. After this action is completed, the user can select the “next” button. This will take the user to the “Threshold Tab”. The user will be required to navigate to Section 5, Navigating the Threshold Tab on Pg.61 of the thesis.

The rest of this section will contain instructions on what to do if the user chooses option “NO” in the calibration parameters question (**Figure B.10**).

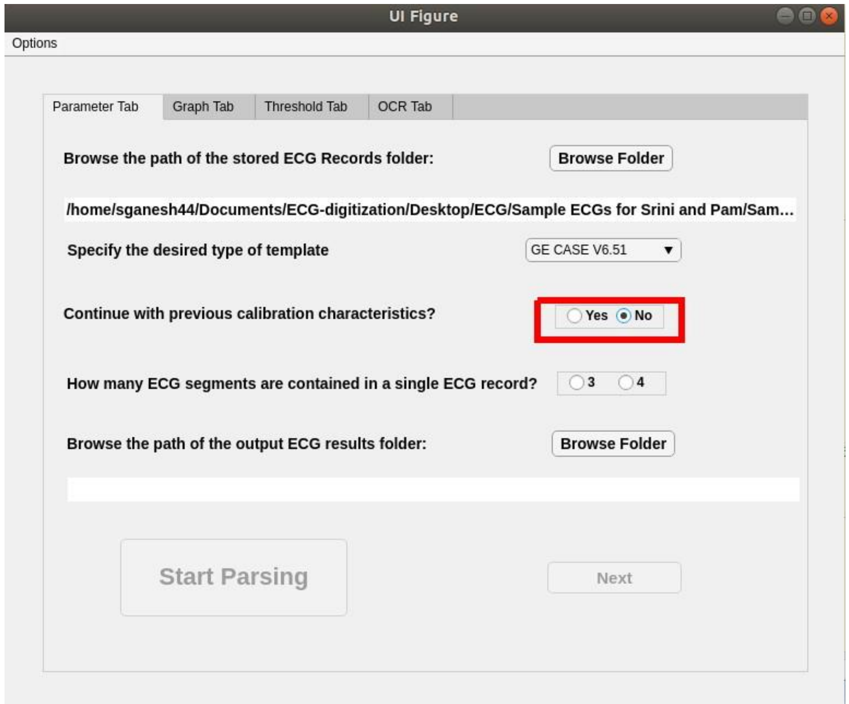

Figure B.17 The user chooses “NO”, and to calibrate the parameters of the ECG template instead. The procedure is identical to the “YES” case, with subtle differences as outlined in the next few figures.

The next steps to be taken are the same as outlined in **Figure B.13**, **Figure B.14** and **Figure B.15**.

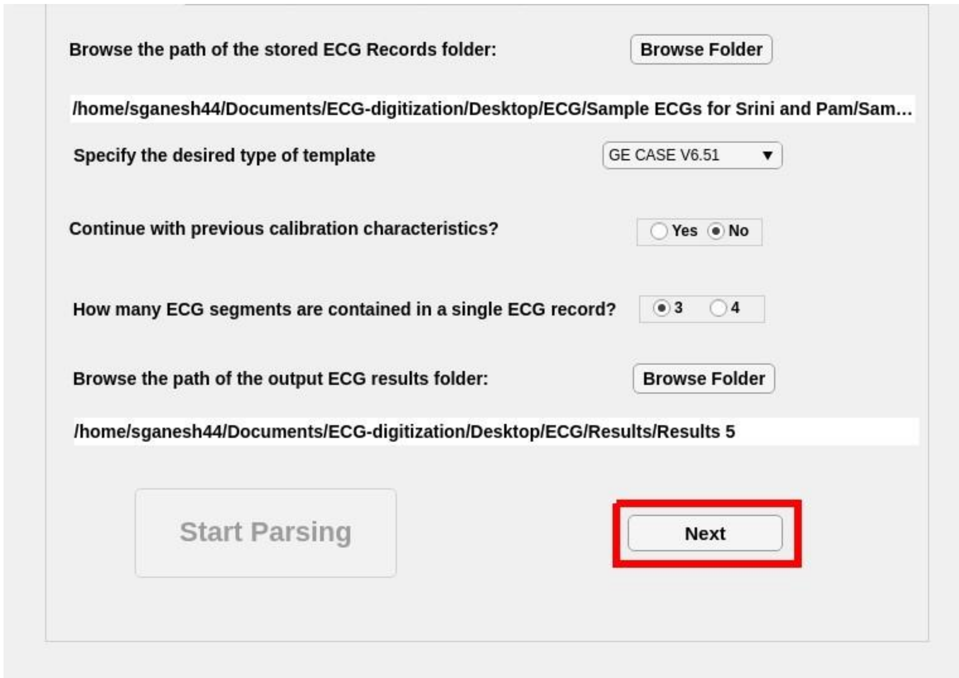

Figure B.18 The user can then press “next” button which will take them to “Graph Tab” on page 54, where they will crop and select salient points of the ECG record.

Section 4
Navigating the Graph Tabs

Only if the user chooses "NO" as the calibration option, will they be redirected to the section, "Graph Tab" to first crop, and then parse the images. The user does not need to utilize this section if not.

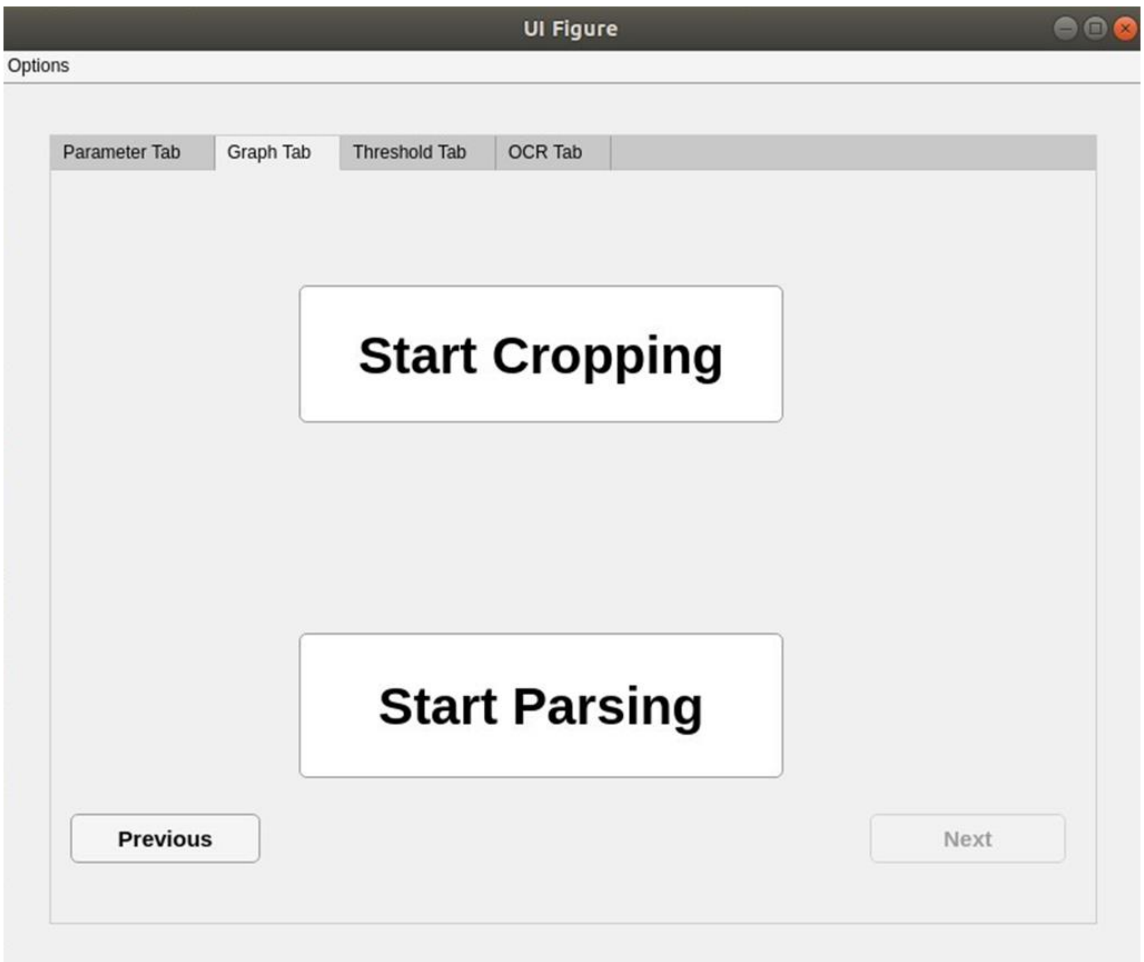

Figure B.19 This is the "Graph Tab", which is mainly utilized for calibration of ECG records.

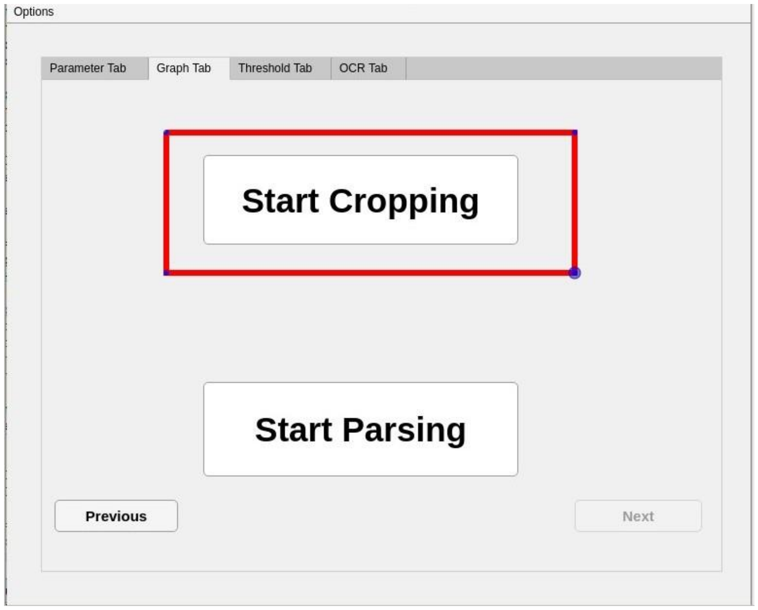

Figure B.20 The “Start Cropping” Tool needs to be chosen first.

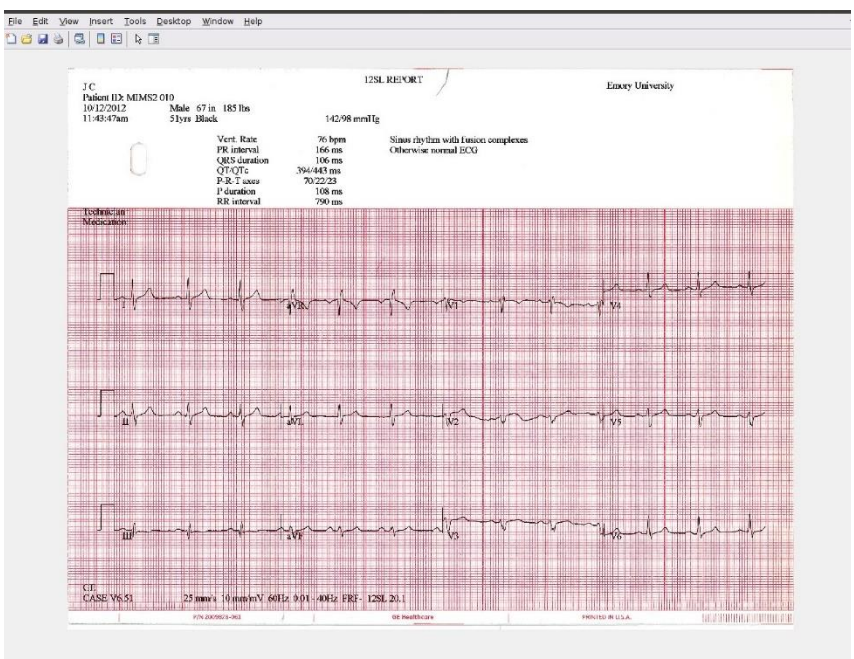

Figure B.21 The following window will pop-up. The user will be required to specify the region in which the ECG signals are likely to appear in.

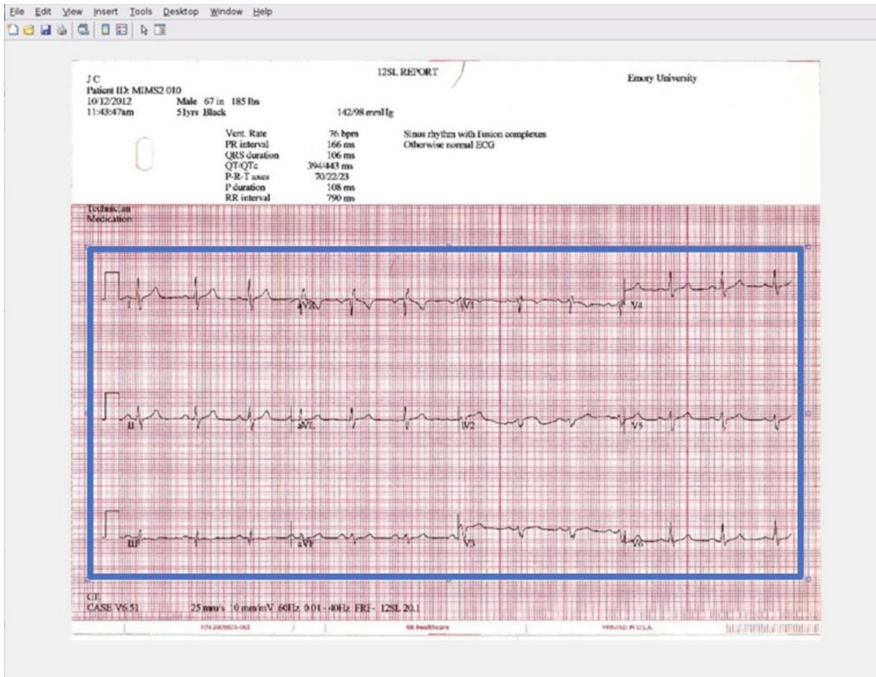

Figure B.22 The user will be required to draw a rectangle (highlighted in blue) around the segments.

The blue line encapsulating the segments is the “cropping rectangle”, in the above picture. Once the cropping rectangle is drawn, the user is required to “right click” on the mouse and select “Crop Image”. Once the image is cropped the user needs to highlight some salient points on the cropped image, which will appear in another pop-up window.

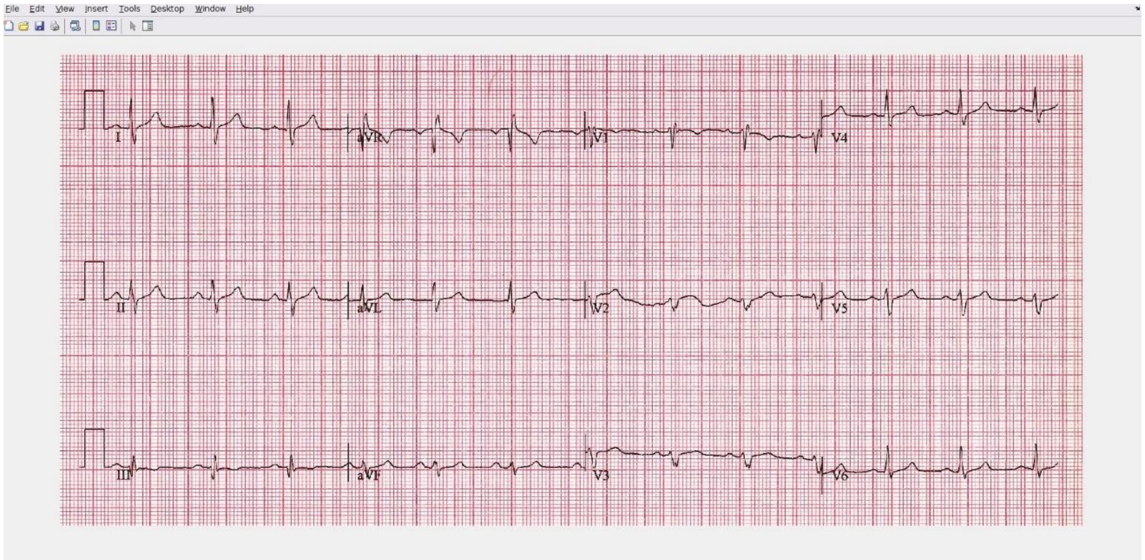

Figure B.23 Once the cropping is done, another window immediately pops up and the user will be required to pick out salient points.

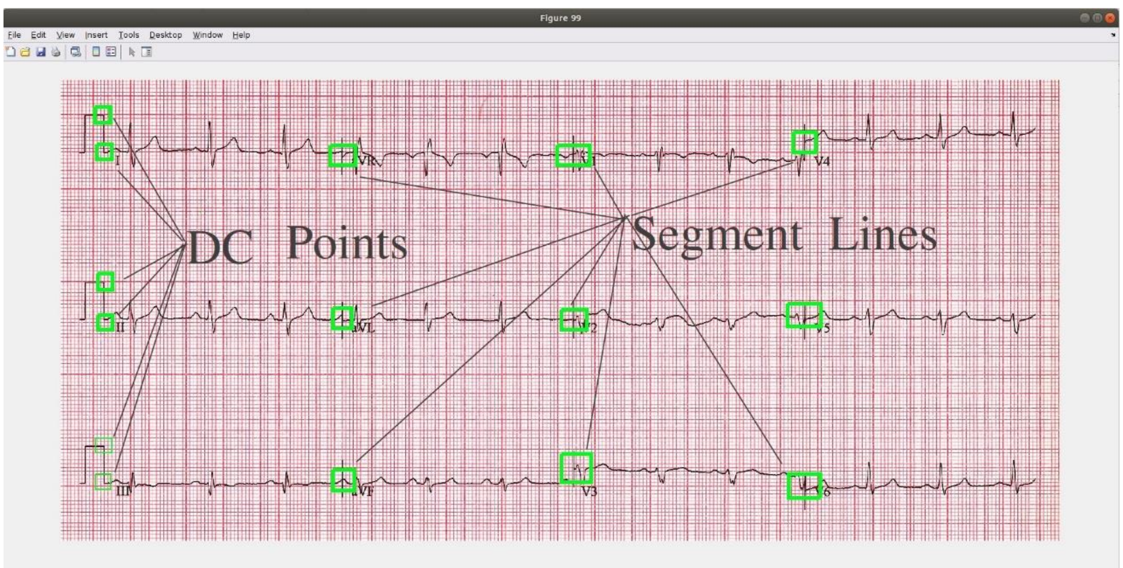

Figure B.24 The salient points in question, are the right vertices of the DC pulse, and the lines separating the ECG segments. The salient points are highlighted in green, in the above image.

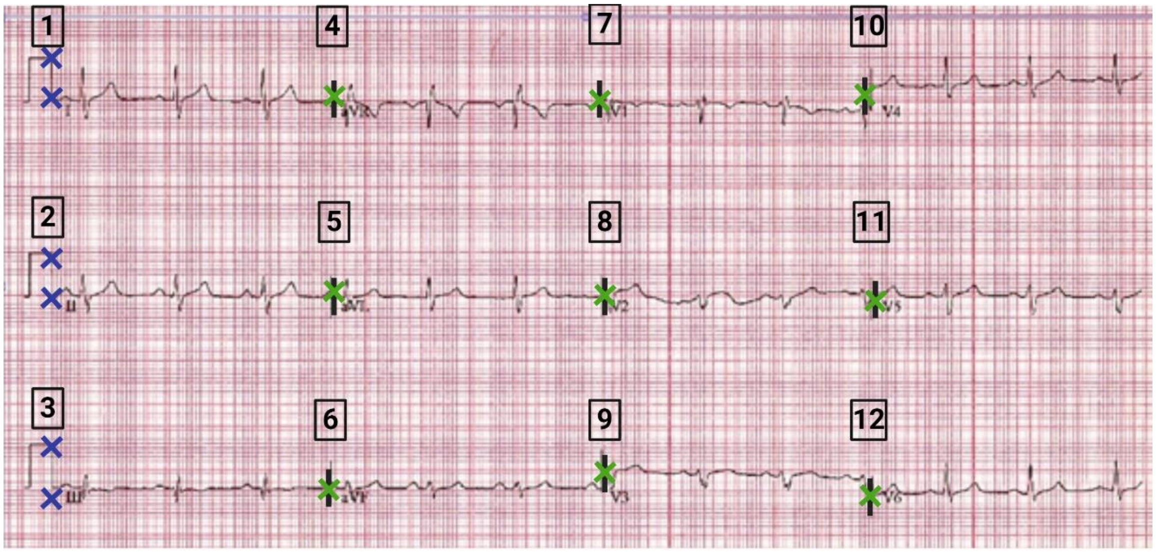

Figure B.25 The user is required to specify the salient points in an ordered manner, depicted by a sequence of numbers in the figure.

Once the points are specified, the user can press “Enter” to exit. If the user wants to delete a few points previous specified, “Backspace” can be pressed to delete the previous selection. The final cropped image, before selecting enter, should look like the following. The blue crosses are faint but should be visible upon close inspection (**Figure B.26**).

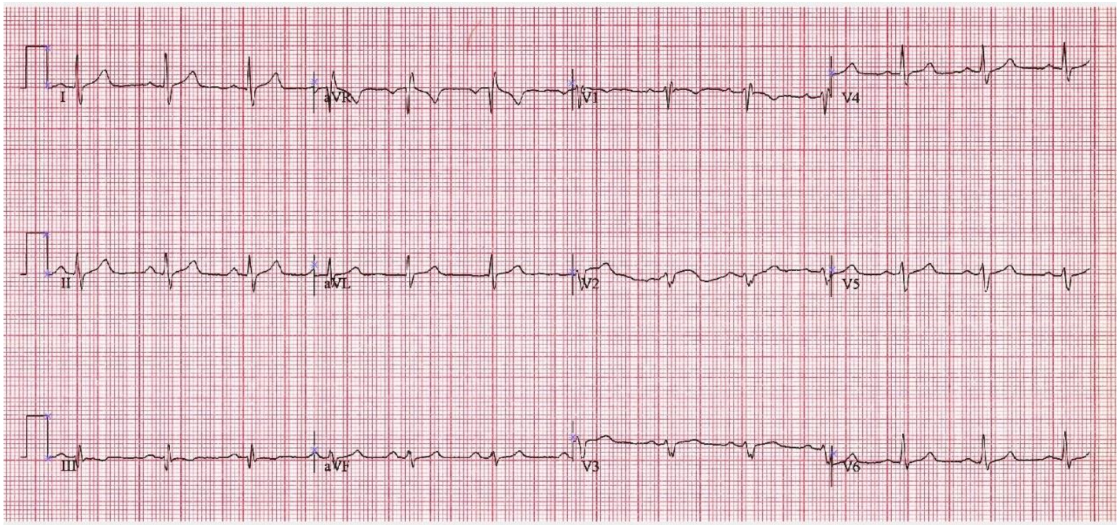

Figure B.26 A realistic depiction of what to expect upon selection of salient points, with faint blue crosses positioned at the salient points.

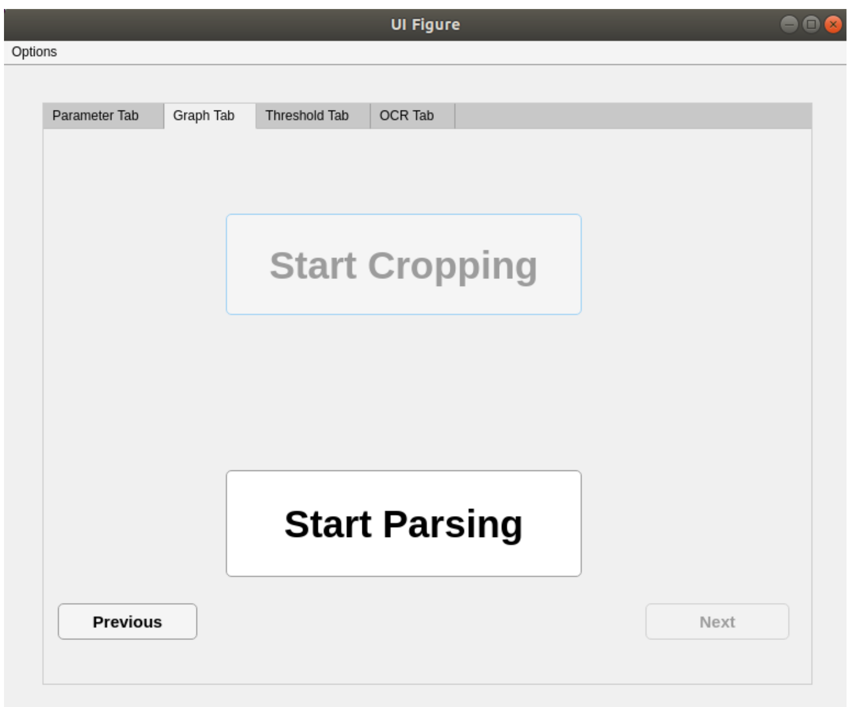

Figure B.27 The functionalities associated with "Starting Cropping" button function comes to an end. The user is required to select "Start Parsing" button.

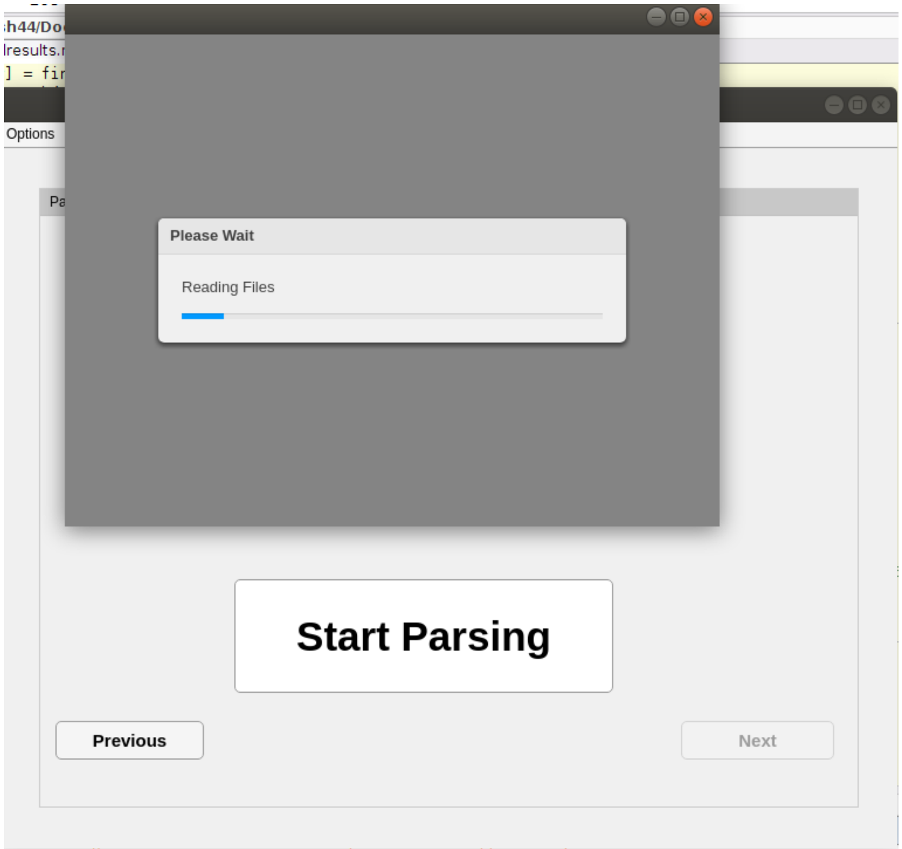

Figure B.28 A pop-up window depicting the progress of “parsing function”.

A pop-up window will be visible, after which the user can select the next button to go to the Section 4, which is the Threshold Tab on page 61.

Section 5
Navigating the Threshold tab

This section helps the user navigate the Threshold section of the ECG App.

Now that the calibration of the ECG records is complete, other parameters to do with threshold have to be selected by the user.

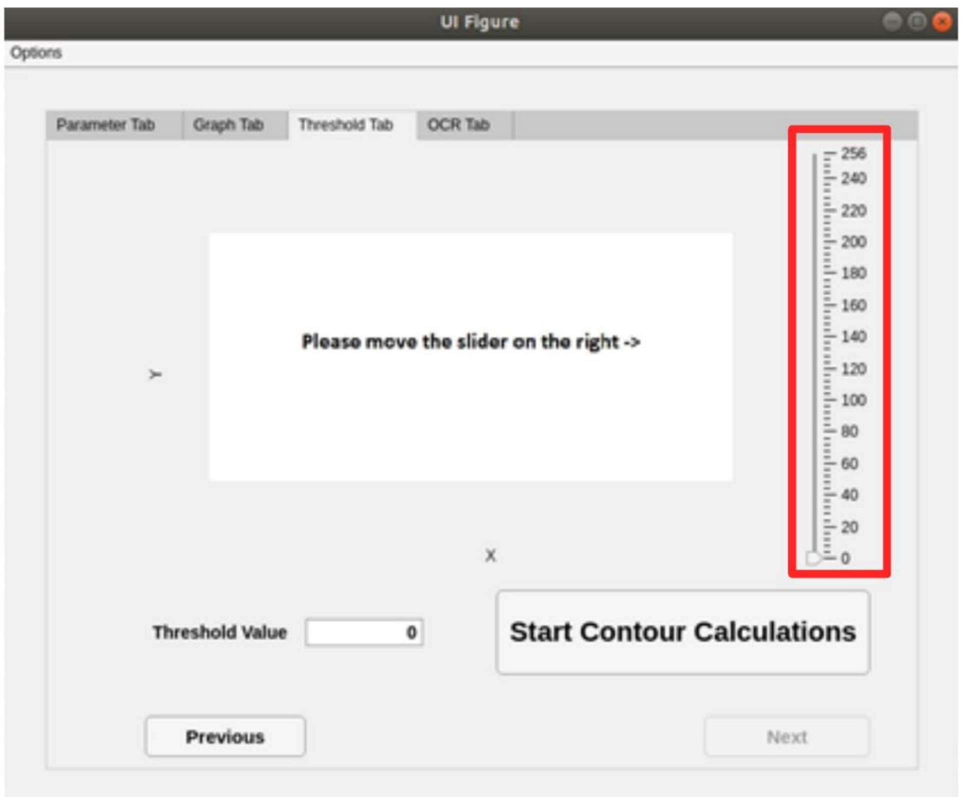

Figure B.29 The threshold can be navigated by using the slider on the right.

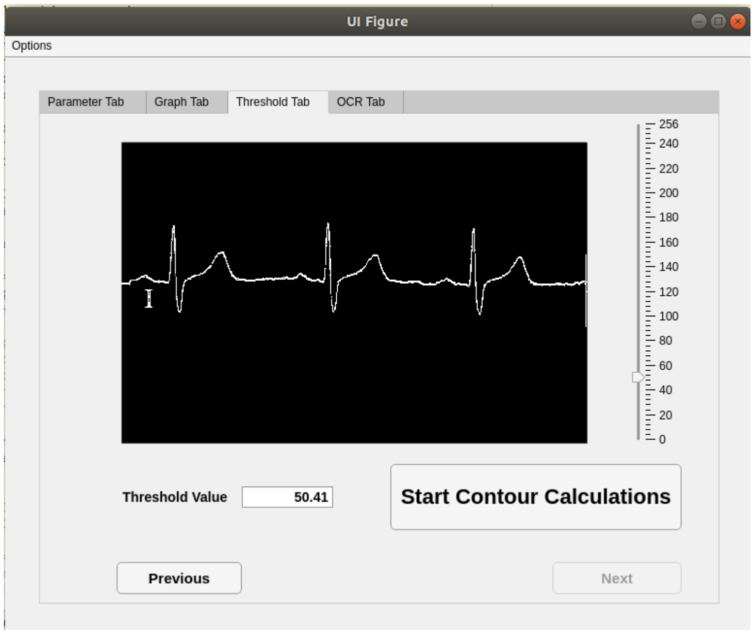

Figure B.30 Once the slider button is moved, the thresholded image appears in the threshold tab.

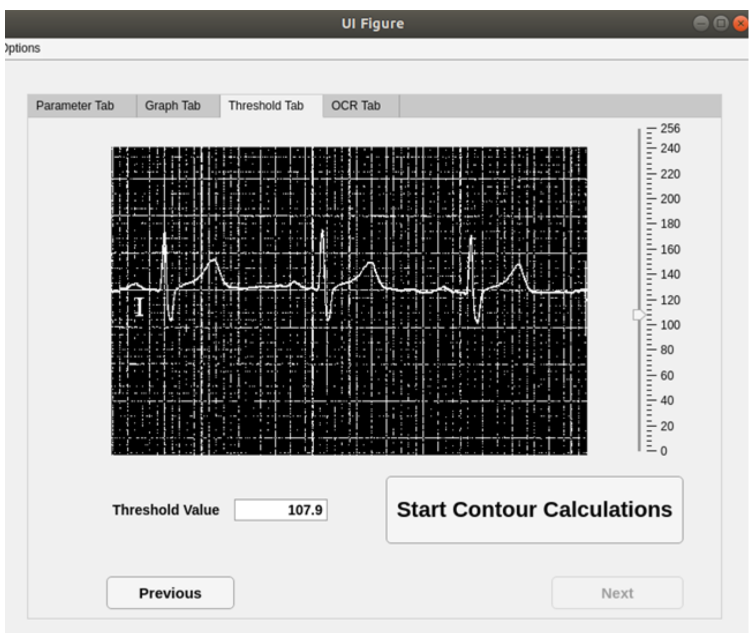

Figure B.31 The threshold must not be too large, for the grid will not be removed completely.

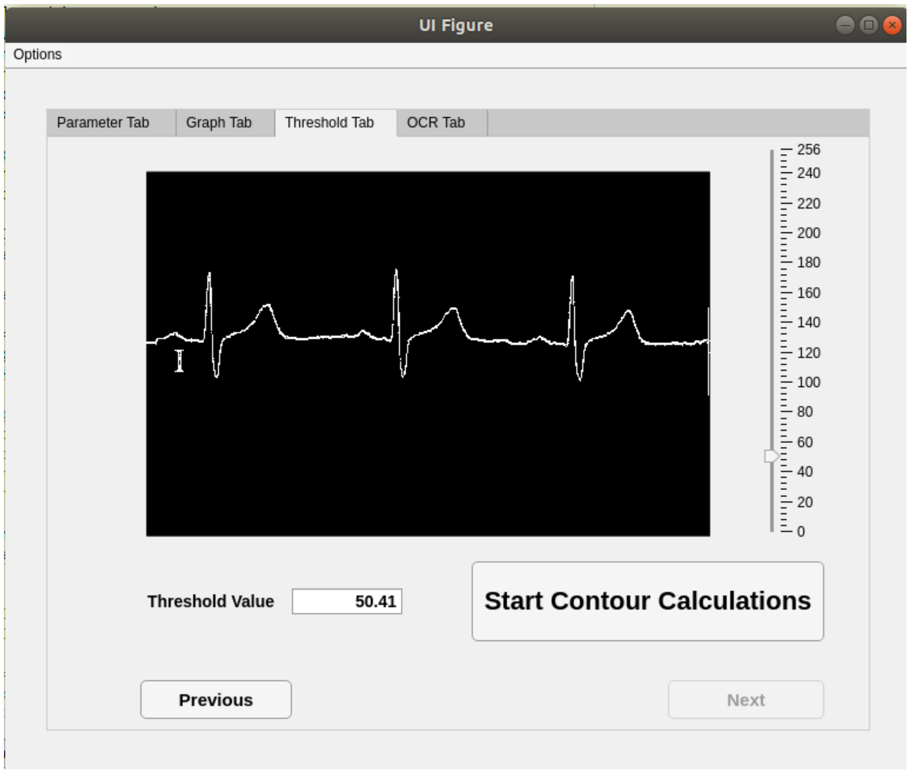

Figure B.32 If the threshold selected is less than the optimal value, the image may look smooth, but the signal strength of the ECG decreases.

The optimal value of threshold would be that value beyond which you see noise infiltrating the image, and the beginnings of the salt and pepper noise. The signal needs to be at its strongest while the noise must be minimum, and a delicate balance between the two must be struck.

Figure B.33 An example of an optimal threshold selection for the ECG signal.

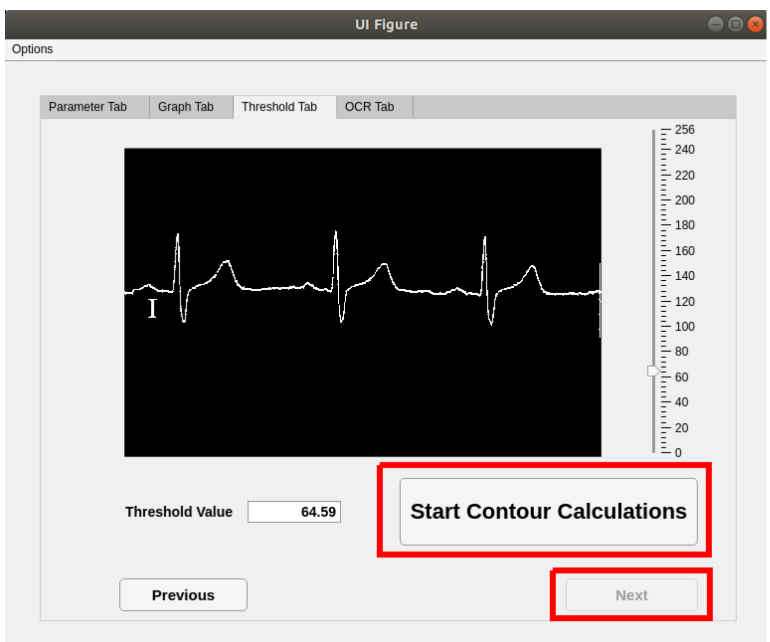

Figure B.34 The user needs to select "Start Contour Calculations" button once the user is satisfied with the threshold. A pop-up window will appear. The "Next button" can be pressed to go to the next OCR tab.

Section 6

OCR Tab

The OCR tab exists to give the user an option of trying out the “Character Removal” feature.

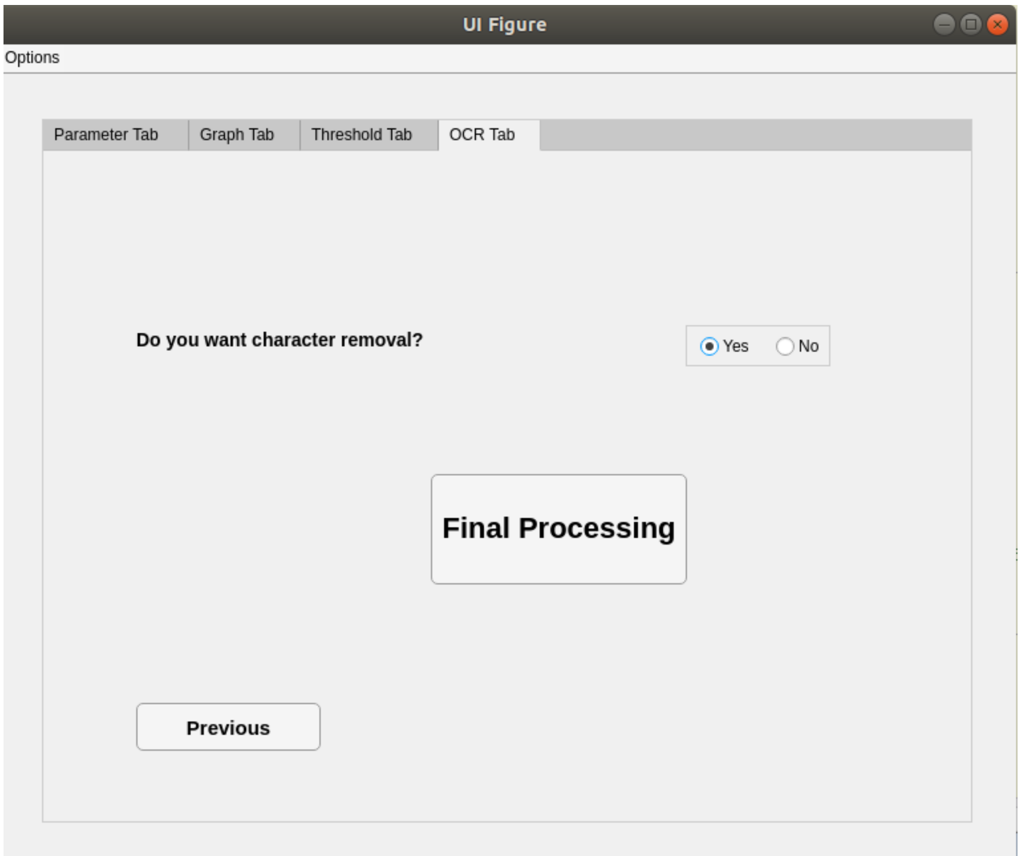

Figure B.35 Character removal can be involved if required. Then ‘Final Processing’ must be selected, and the results will be stored in the earlier specified folder

Section 7
Understanding the Results Organization

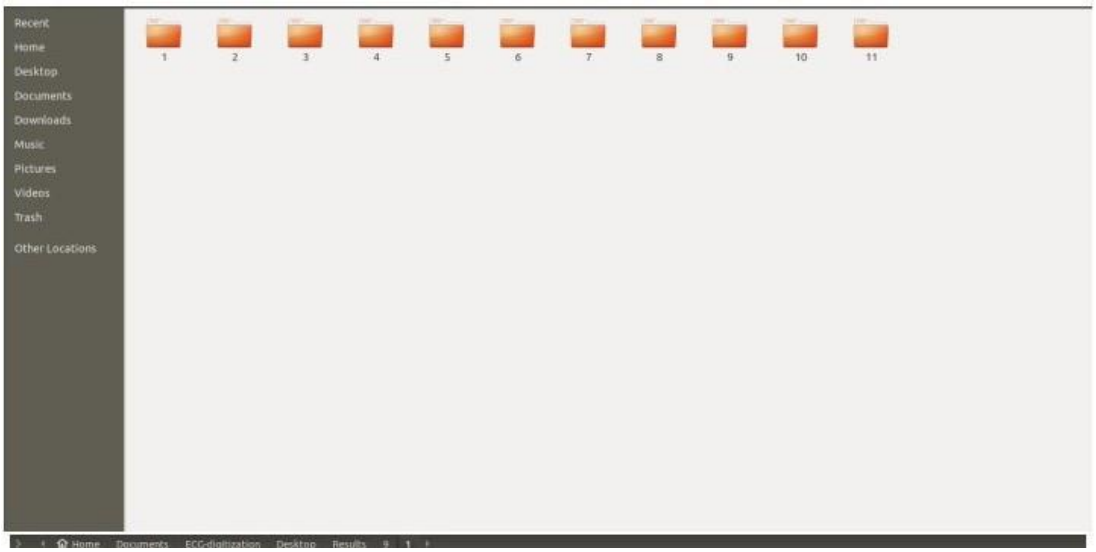

Figure B.36 Each ECG paper record will have its own folder, in which the digitized ECG records, along with the extracted patient demographic information is stored.

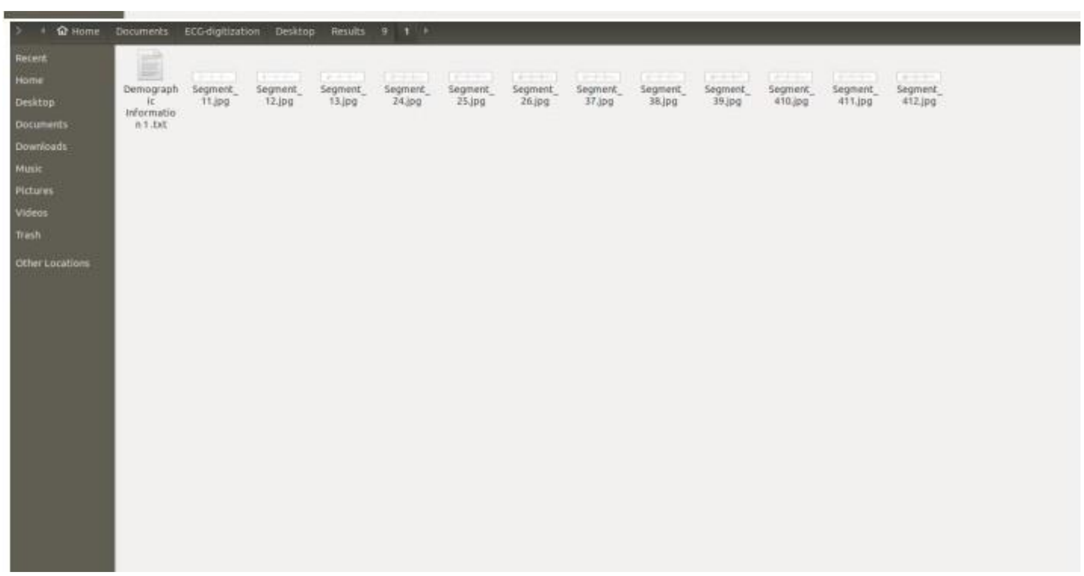

Figure B.37 Inside each folder, demographic text information and the digitized segments are present.

The order in which the segments are saved follows the same order as depicted in Figure B.25. For example, “Segment_11” refers to the first segment, next to DC pulse 1. Segment_12 refers to the one directly beneath it. “Segment_21” refers to the segment adjacent to the “Segment_11”.

Section 8
Reset Button

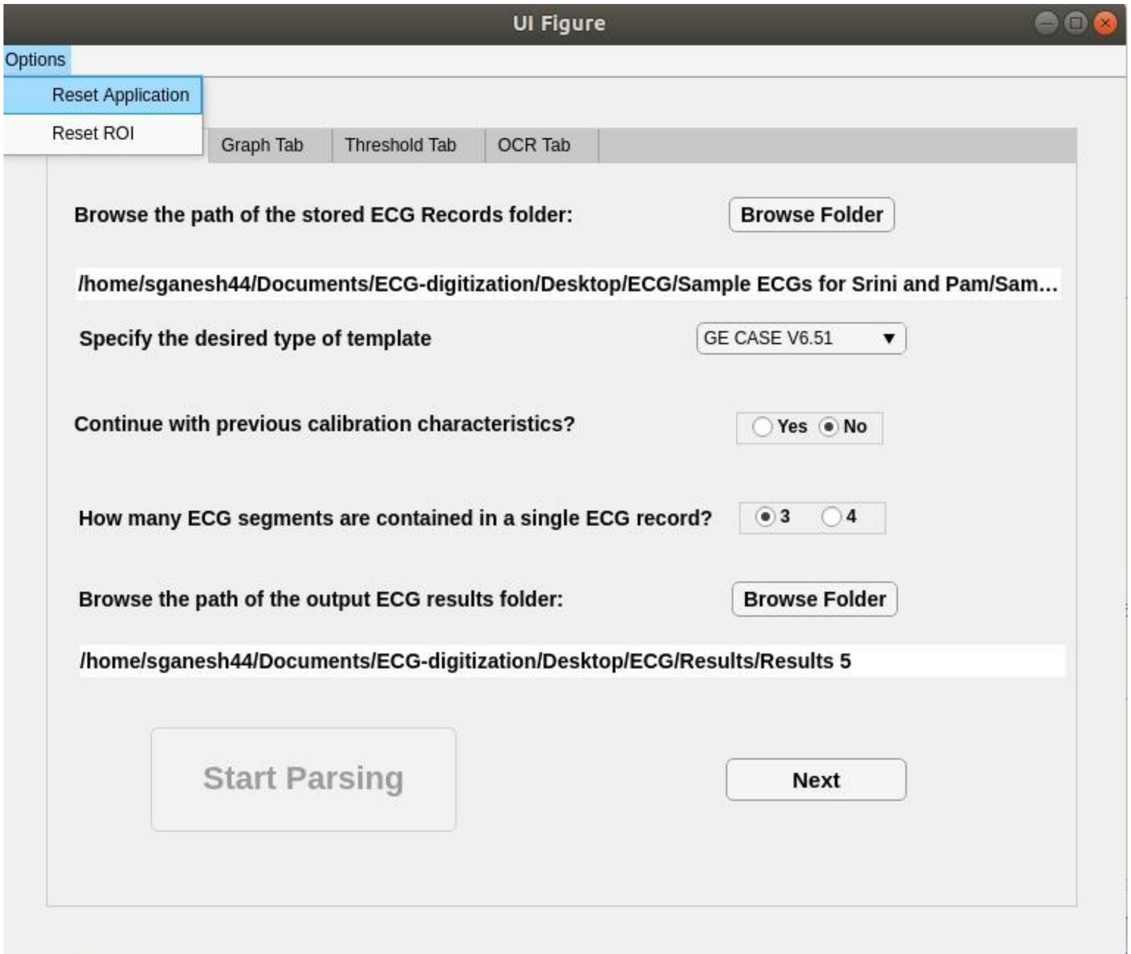

Figure B.38 The reset button is located on the top of the GUI. The user needs to select the option button, and then select “Reset Application”. All the fields will be wiped out and the GUI should return to the Parameter Tab

APPENDIX C

OCR MANUAL

This appendix details steps to create a library of training data using OCRtrainer, in MATLAB.

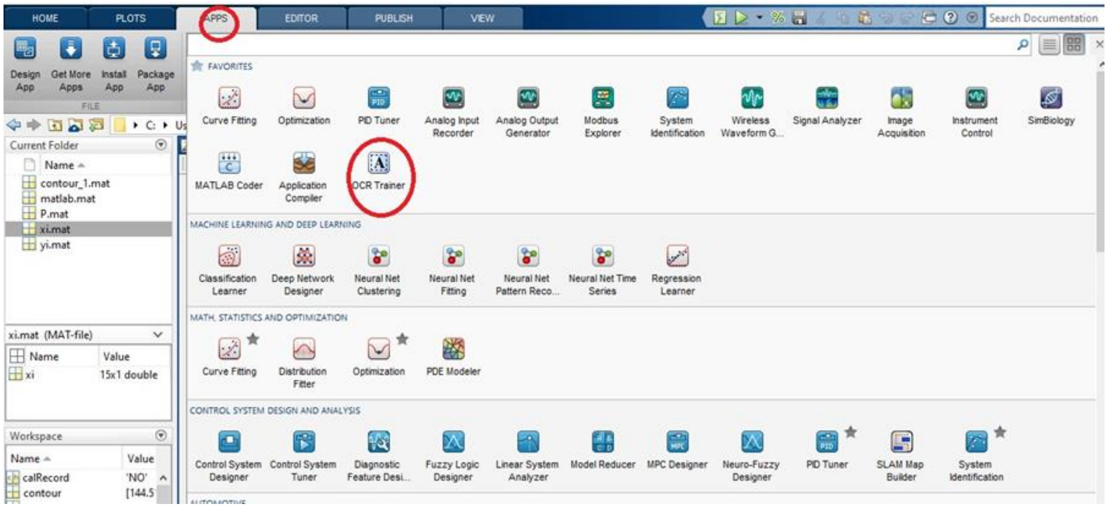

Figure C.1 In MATLAB, the user is required to go to APPS -> OCR Trainer.

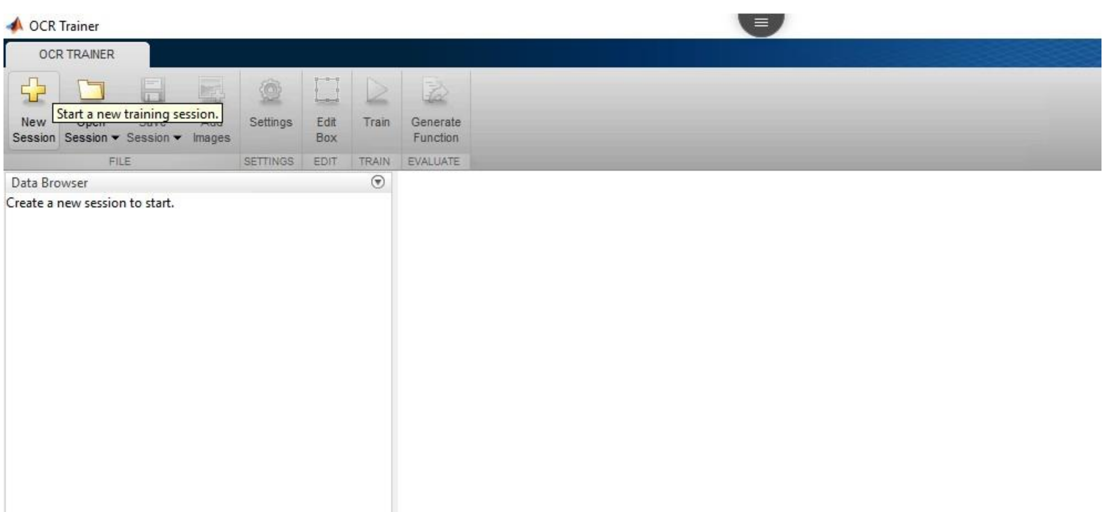

Figure C.2 The following window opens up, and the user has to click "New Session".

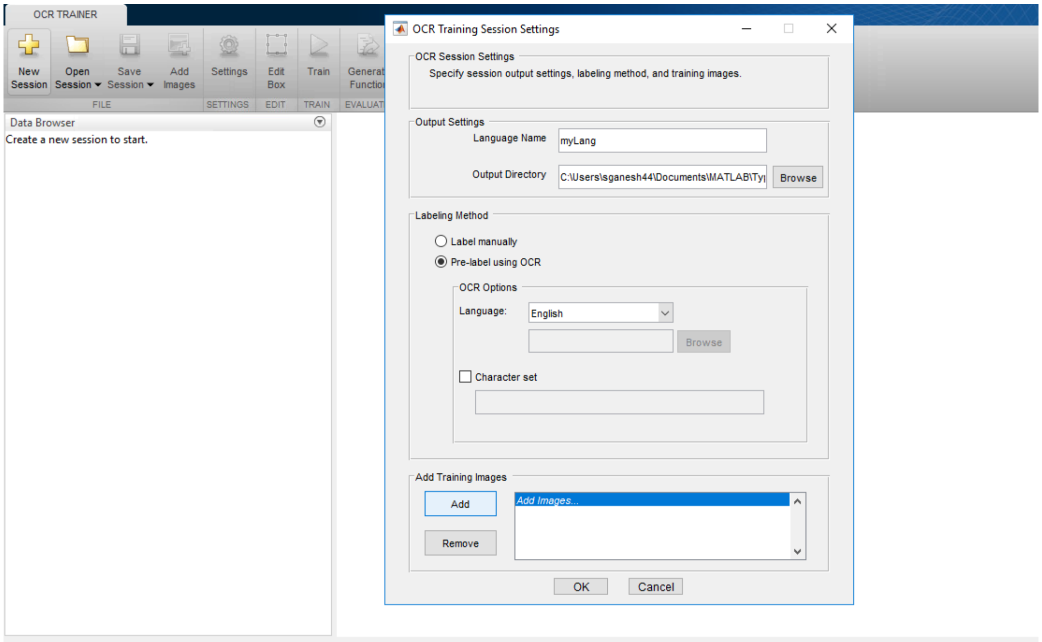

Figure C.3 The user can tweak parameters like where the language library file must be stored, whether the letters must be segmented manually/OCRtrainer etc. The user is also required add images, at this step.

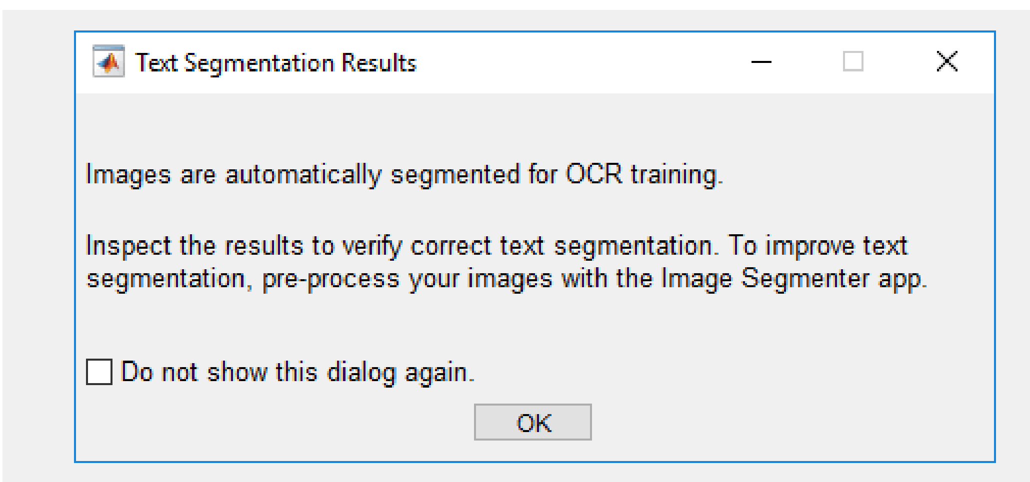

Figure C.4 This window will then pop-up indicating images are going to be segmented.

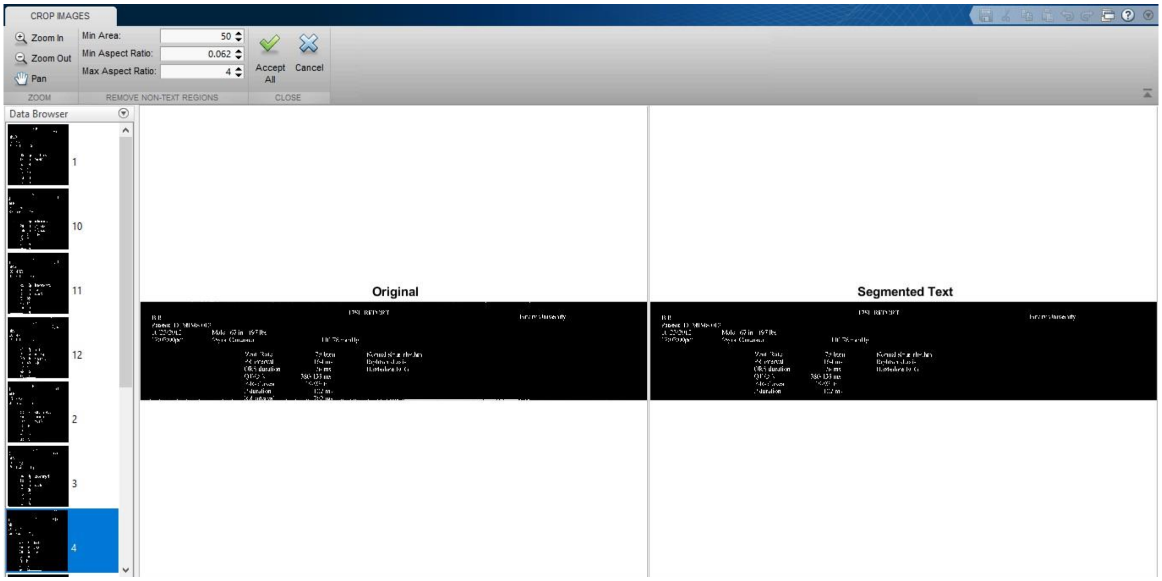

Figure C.5 The software then requires the user to look at the images and decide if the desired text is being segmented.

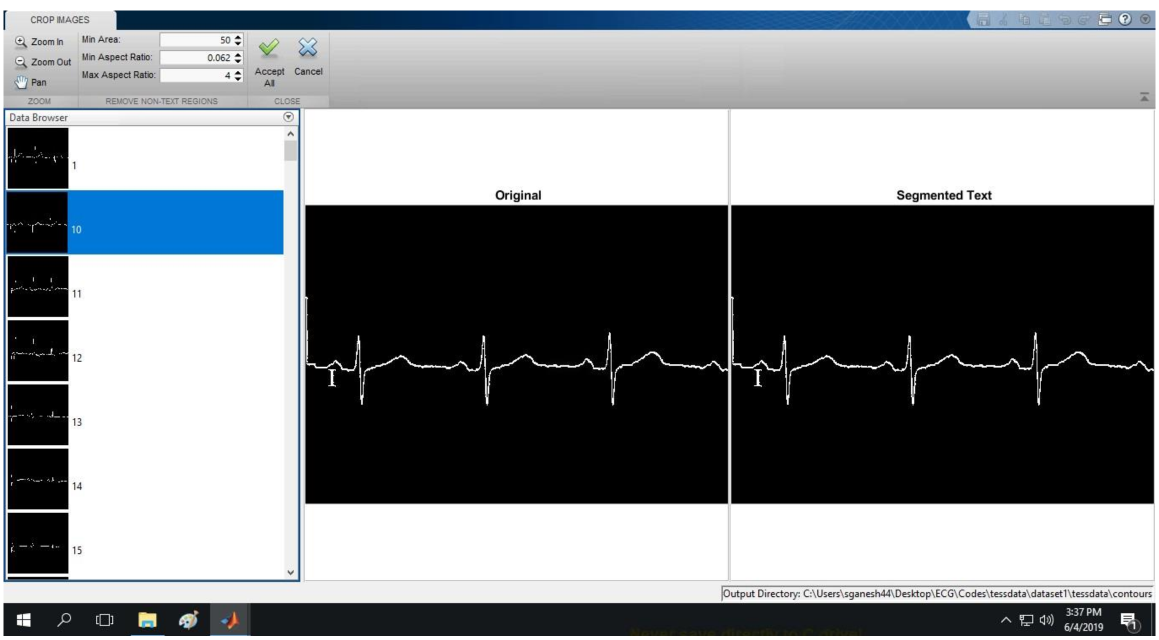

Figure C.6 Sometimes the text is not recognized, like in the following case. The user must correct such cases.

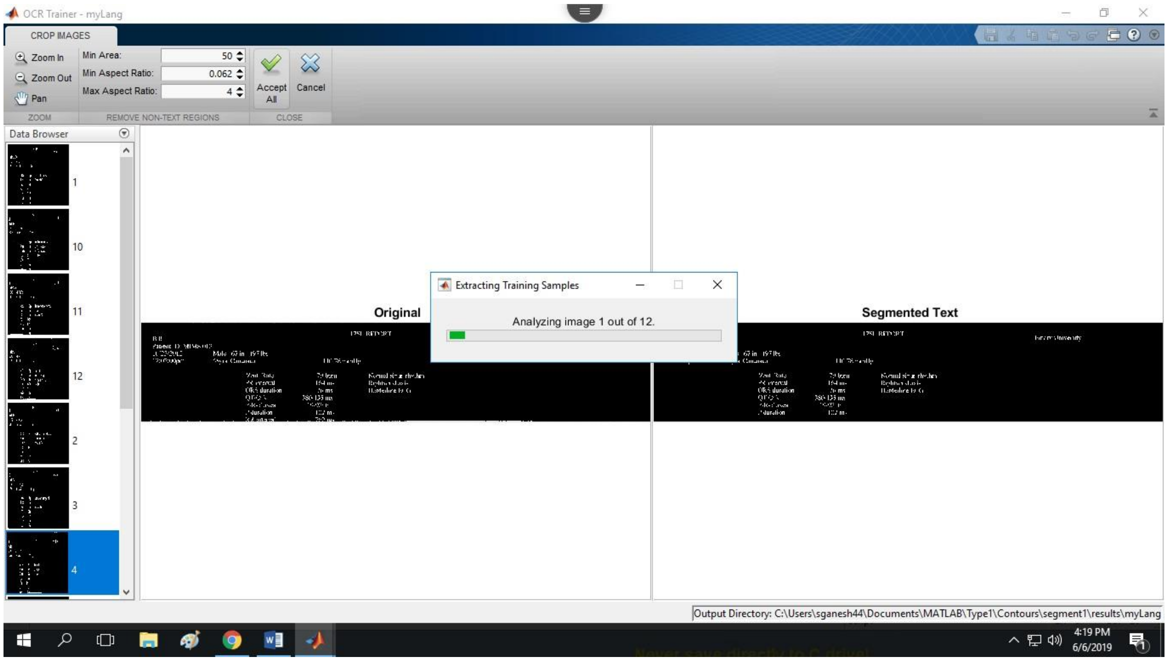

Figure C.7 The OCRtrainer then extracts and recognizes the character.

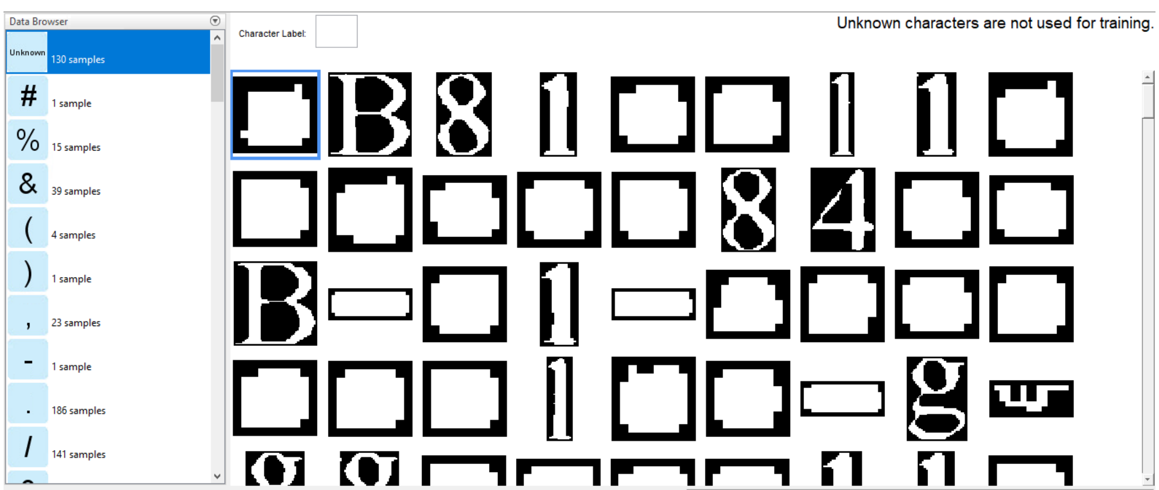

Figure C.8 The user is required to relabel some characters which are mislabeled.

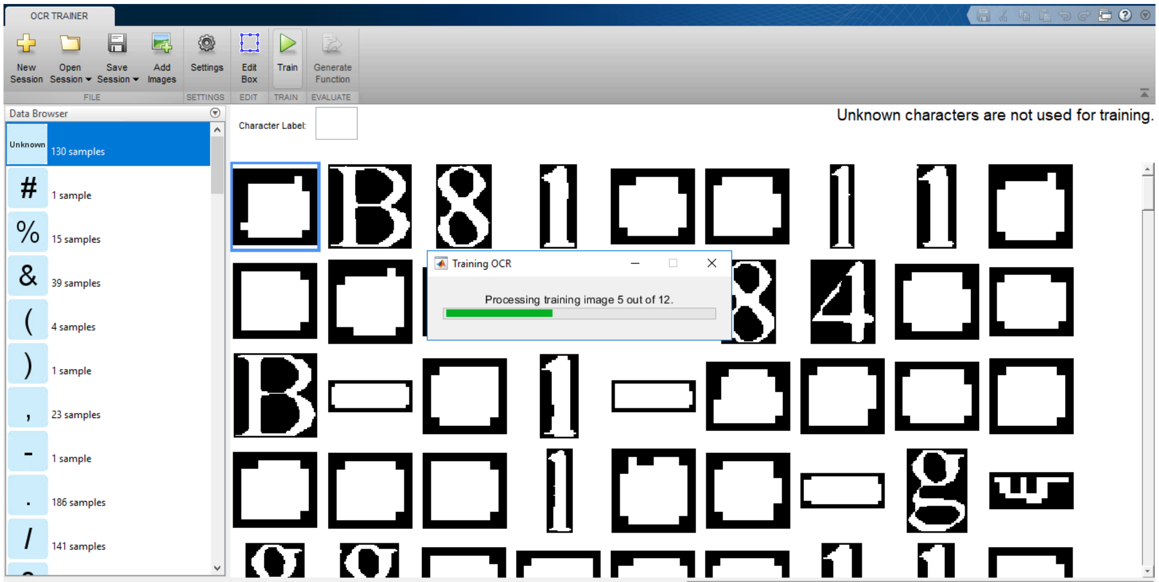

Figure C.9 Then the user can click the "TRAIN" button, and training will take place.

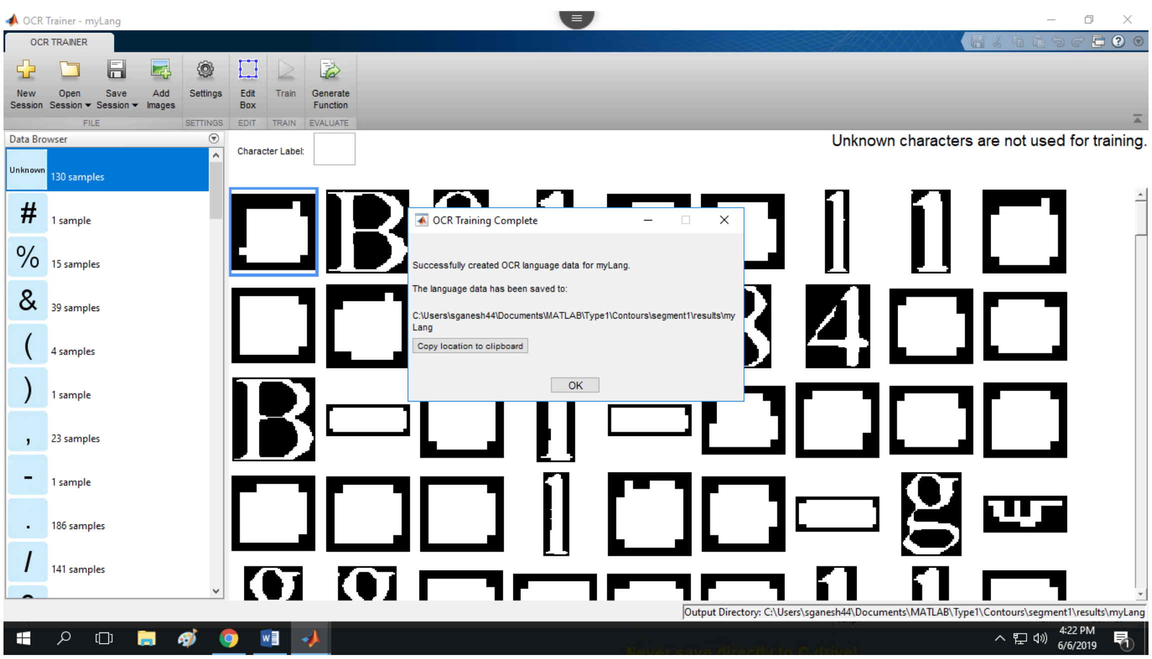

Figure C.10 The pop-up window indicates that the training is complete.

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